The effects of environmental regulations on waste trade, clean innovation, and competitiveness in a globalized world

Damien Dussaux

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Damien DUSSAUX

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Les effets des politiques environnementales sur le commerce international des déchets, l'innovation verte, et la compétitivité, dans un monde globalisé

Directeur de thèse : **Matthieu GLACHANT**

Jury

M. Pierre Mohnen, Professor, Maastricht University	Président
M. Mouez Fodha, Professeur, Paris School of Economics	Rapporteur
M. Massimiliano Mazzanti, Associate Professor, University of Ferrara	Rapporteur
M. Thomas Sterner, Professor, University of Gothenburg	Examinateur
M. Matthieu Glachant, Professor, MINES ParisTech	Examinateur

T H È S E

MINES ParisTech
Cerna
60 Boulevard Saint Michel, 75006 Paris

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Introduction

Policy context and research question

International trade has been growing very rapidly during the last decades.[1] A major determinant of this growth has been trade liberalization following the different General Agreement on Tariffs and Trade (GATT) rounds.[2] These agreements ensure that every country that is member of the World Trade Organization (WTO) cannot impose a tariff that is higher than the Most Favoured Nation (MFN) tariff on another WTO member. Additionally, countries and group of countries have been negotiating Free Trade Agreement (FTA) or Custom Union (CU) in order to suppress barriers to trade, capital movement, and more rarely movement of labor. These regional trade agreements are not anecdotal and cover a large part of the world economy. For instance, the European Economic Area (EEA), that regroups 30 countries, accounts for 24% of world GDP in 2014.[3] The North American Free Trade Agreements (NAFTA) between Canada, the United States, and Mexico accounts for 26% of world GDP in 2014. The Association of Southeast Asian Nations (ASEAN)-China Free Trade Area (ACFTA) between 10 ASEAN countries and China accounts for 16% of world GDP in 2014.

[1] World trade weighted 4% of world GDP in 1988 and weights around a quarter of world GDP in 2013. Between 1988 and 2013, world trade in goods grew by 14% per year on average while world GDP grew by 6% per year on average. These figures are based on author calculation from the United Nations Comtrade database.

[2] Since 1947 an increasing number of countries have agreed in reducing tariff barriers on international trade. A total of 8 negotiations rounds have been completed. The last round completed in 1986, called the Uruguay round, gave birth to the WTO and led to a reduction of tariffs by 40% between 123 countries.

[3] This share is the ratio between the sum of GDP of the countries belonging to the trade block and world GDP. Author's calculation based on GDP in current USD from the World Bank.

Since the ten pages written by David Ricardo in 1817 on the principle of comparative advantage in his book *Principles of Political Economy and Taxation*, most economists have advocated that countries benefit from trade. These gains from trade come from the specialization of countries in producing different set of goods. To maximize these gains, countries should specialize in the production of goods for which they have a comparative advantage that is in the goods for which they are the most productive given other countries' productivity. Thus, free trade should be more efficient than autarky. This reasoning provides a rational for phasing out barriers to trade.

However, trade liberalization faces the criticism of different groups of opponents. Trade liberalization generates both winners and losers within each trading countries. Industries that would lose from freer trade actively lobbies to maintain trade policies that protect them from foreign competition. Governments may enact trade policies because they seek to protect domestic jobs. In addition to these historical opponents to trade liberalization, new opponents have emerged during the second half of the 20th century. Several Non Governmental Organizations (NGOs) have been advocating that trade liberalization generates bad side effects regarding two main topics: worker rights and the environment. Many fear that international competition gives countries incentives to increase their comparative advantage by adopting lax labour and environmental regulations that result in worse working conditions and more pollution.

While these phenomenons are commonly known as social and environmental "dumping", economists have framed the debate around different concepts. One of the most debated concept among economists in the trade and environment field is the "Pollution Haven Hypothesis" (PHH). The PHH is formulated by Taylor (2005): "Liberalized trade in goods will lead to the relocation of pollution intensive production from high income and stringent countries, to low income and lax countries".[4] Copeland and Taylor (1994)'s seminal work show that if differences in environmental regulations are the only motive for trade and that

[4] As pointed out by Taylor (2005), environmental dumping and PHH are distinct phenomena. Environmental dumping refers to the phenomenon where countries engage in strategic behaviours that result in laxer environmental regulations. A "race to the bottom" can take place and results in a loss of global welfare in comparison to a situation where countries adopt cooperative behaviors.

trade does not equalize factor prices, then trade liberalization increases world pollution. As environmental regulations is only one determinant of comparative advantage, the PHH is an empirical question. For economists, it has been hard to test the PHH empirically. This is because any change towards freer trade is not exogenous since it depends on current trade patterns.[5]

To face this empirical issue, economists have sought to test another hypothesis called the "Pollution Haven Effect" (PHE) which is a necessary but not sufficient condition for the PHH to be true. The PHE states that cross-country difference in environmental regulatory stringency leads industries to relocate in lax countries other things equal. In other words, environmental regulations have a significant impact on comparative advantage. The PHE is different from the PHH because the latter focuses on the impact of trade liberalization on pollution level and the former is interested in environmental regulations as a determinant of comparative advantage. While early studies found no significant PHE, several recent studies provide evidence of a significant PHE (Xing and Kolstad, 2002; Javorcik and Wei, 2004; Cole and Elliott, 2005; Ederington, Levinson, and Minier, 2005; Levinson and Taylor, 2008; Kellenberg, 2009; Wagner and Timmins, 2009; Millimet and Roy, 2011; Kheder and Zugravu, 2012; Tang, 2015).[6] These evidence make the PHH more plausible. A particularly interesting outcome of the PHE is the situation of carbon leakage where the countries introducing stricter climate policies lower the competitiveness of their firms as well as fail to reduce global Green House Gas (GHG) emissions. Given the future risks and potentially large impacts that climate change involves, carbon leakage receives an important policy attention.[7]

Unlike trade in energy intensive goods, trade in waste has received so far little attention in the PHE literature. While economists focused on the relocation of factories that emit pollution, they have neglected the fact that countries could export polluting inputs as well. As waste treatment or non treatment generates pollution emissions, waste are therefore pol-

[5]As a result, few studies address directly the PHH (see for instance Antweiler, Copeland, and Taylor (2001); Dean (2002); Ederington, Levinson, and Minier (2004); and Kahn and Yoshino (2004)).

[6]See Dean (1992), Levinson (1996a) and Copeland and Taylor (2004) for reviews of early empirical studies.

[7]See the working group II and III contribution to the Intergovernmental Panel on Climate Change (IPCC) Fifth assessment report for the physical and economic impacts of climate change.

luting inputs. In fact, trade in waste is far from being negligible. In 2010, 5.8 million tons of waste crossed a border. More importantly, it is growing rapidly with a pace of 6% per year on average from 2002 to 2010.[8] Similarly to the PHE, cross-country differences in environmental regulations could direct waste flows towards lax countries and generate "waste havens" in which waste treatment and careless waste accumulation engender important pollution. In the first chapter of this dissertation, I investigate how cross-country difference in waste taxes impacts the bilateral trade in waste.

Environmental regulations may not only affect pollution emission levels and pattern of trade in intermediate and final goods or trade in waste but may also impact trade in raw materials. Part of the increase in extraction costs of mineral resources is due to environmental regulations. Other things equal, countries with strict environmental policies import raw materials from foreign countries with less stringent policies. However, environmental policies also stimulate waste recovery that is a form of domestic production of raw materials. In the end, recycling policies may lower the import demand in raw materials. In Chapter 2, I use country-level data to measure the side-benefit of waste recycling on the balance of trade.

The shift from resource intensive technologies to resource efficient technologies is also a major concern in the economics of growth. For the last decades, green Non-Governmental Organization (NGOs) concerned with ecology have opposed economic growth and environmental preservation which ultimately conditions the human survival. These groups often argue that only zero growth or even degrowth can allow for a sustainable development. Recent economic theories emphasizes the role of innovation and particularly the role of green innovation in economic growth. Acemoglu, Aghion, Bursztyn, and Hemous (2012)'s seminal work shows that when dirty and clean inputs are sufficiently substitutable, sustainable growth can be achieved using a temporary taxes on dirty production. The environmental tax redirects innovation toward the clean industry. This phenomenon is called "directed technical change" in the economic literature.

Understanding the determinants of clean innovation is an important matter given the pressing challenges posed by climate change and other environmental issues. For instance,

[8]These figures are for legal trade in waste only.

this is critical in the case of climate change. As green technologies contribute to abate future emissions of greenhouse gases, their timing is key: it determines the cumulative levels of greenhouse gas in the atmosphere and hence the risk of dangerous climate change.[9] It is not surprising then that providing incentives to develop new clean technologies has become a focus of environmental policy. There are now several empirical evidence that environmental regulations lead to cleaner innovation. Ghisetti and Pontoni (2015)'s meta-analysis shows that 78% of the models from the primary studies find that the environmental policy variable has a statistically significant effect on environmental innovation. However, the international trade dimension of this debate has been introduced only recently. As well as free trade shapes production output worldwide, it may also play an important role in determining innovation output and direction. In Chapter 3, I shed some lights on the impact of trade on innovation. More specifically, I empirically test whether trade with low-production cost countries change the direction of French firms' innovation.

While it is important to know if environmental regulations are successful in reducing pollution emission, it is also essential to know the cost of these regulations. In the political debate, environmental policies are regularly held responsible for destroying firms competitiveness which in turn leads to the destruction of domestic jobs. There are two opposite views on that matter. Economists in line with Porter and Van der Linde (1995) believe that properly design environmental regulation can trigger innovation that may partially or more than fully offset the costs of complying with them. In other words, environmental regulation is neutral or beneficial to firm competitiveness. In contrast, more orthodox economists think that if there was an opportunity to improve productivity, firms would have done it whether they are under the regulation or not. As a result, they believe that environmental regulations can only harm competitiveness.

It is important to know if and how much environmental regulations harm the private sector. This is because, based on this belief, policy makers may be reluctant to introduce more

[9] Timing is especially important as technologies may be path dependent that is it is easier to innovate in clean technologies if these technologies are already well developed. The cost to switch from dirty to clean technologies increases as the path of dirty technologies expends.

stringent environmental regulations that could be beneficial to public health and environment and result in economy-wide benefits. So far, this question is still highly debated because of mixed empirical evidence. The last chapter of this dissertation conducts a comprehensive test of the Porter Hypothesis and provides some insights on the PHE.

The contribution of this dissertation

My Ph.D. thesis contributes to the literature on trade and the environment through several economic analysis of country level and firm level data. I use appropriate econometric methods to address important empirical questions that have either not been investigated yet or that are still subject to an intense debate. In this dissertation, I examine some mechanisms in which environmental regulations could lead to inefficient outcomes under free trade. I also investigate how particular environmental policies such as recycling policies can help to address other concerns at the country level. The Ph.D. thesis is organized along two research axes. The first axis focus on waste policies and their impact on waste and raw material international trade flows.

Waste policies and international trade in waste

In the first chapter of this dissertation, I analyse how cross-country difference in waste taxes impacts the bilateral trade in waste between the member states of the European Union. Concerns about international trade in waste have been reinforced by the publicity given to cases such as the 2006 Ivory Coast toxic waste dump offloaded by the ship Probo Koala, causing the death of 17 inhabitants in Abidjan. Media regularly report on China being the electronic waste basket of the world. Several studies or reports indicate that a large amount of electronic and electrical waste (e-waste) from foreign countries end up in China (Puckett, Byster, Westervelt, Gutierrez, Davis, Hussain, and Dutta, 2002; Chi, Streicher-Porte, Wang, and Reuter, 2011; Hosoda, 2007; Shinkuma and Huong, 2009; Shinkuma and

Managi, 2010).[10] This issue involves many developing countries and not only e-waste.

These concerns are based on consistent arguments: waste is an input for disposal and material recovery activities and economic theory predicts that inputs tend to flow in countries with lower production costs, and environmental regulation undoubtedly exerts a strong influence on waste management costs. Trading waste potentially improves welfare as it makes possible to locate waste disposal and recovery activities where it is cheaper to do so. However, it is socially detrimental if the importing country's comparative advantage stems from insufficient internalization of environmental and health costs. This latter situation corresponds to the "waste haven effect".[11]

A recent paper by Kellenberg (2012) is the first work that tests the waste haven hypothesis.[12] Others either examine domestic trade within the US (Levinson, 1999a,b; Deyle and Bretschneider, 1995), or they deal with international trade, but consider the influence of other variables such as the participation in the Basel Convention (Kellenberg and Levinson, 2013) or income per capita (Baggs, 2009).

Chapter 1 differs from Kellenberg (2012) in three major ways. First, our definition of waste is different. I define "unprocessed waste" as waste that have not been landfilled, incinerated or recovered yet. In contrast, secondary raw materials produced by waste recovery are processed waste used as inputs in the manufacturing sector. Kellenberg (2012) pools unprocessed waste and secondary raw material in his estimations. Here, I focus only on waste that are unprocessed. This is because unprocessed waste and secondary raw materials obey radically different industrial logics and the impact of environmental regulations on waste processing is much more important than on secondary raw material utilization.

The second difference between Chapter 1 and Kellenberg (2012) is the empirical strategy used. Kellenberg (2012) estimates directly the impact of cross-country difference in regulatory stringency on bilateral waste flows. In Chapter 1, I proceed in two stages to quantify

[10]See Wang, Kuehr, Ahlquist, and Li (2013) for a recent report on e-waste in China.

[11]As formulated by Kellenberg (2012).

[12]It is also worth mentioning a few theoretical works such as Kohn (1995) or, more recently Kinnaman and Yokoo (2011) and Bernard (2011) who focus on some very specific waste trade (used electronic goods). They confirm the result of Copeland (1991) who shows that restrictions on trade such as those in the Basel Convention can improve welfare in the presence of illegal disposal of waste.

the waste haven effect. First, I estimate using an econometric method how much waste management costs differences influence trade flows. In the second stage, I simulate the impact of waste taxes on waste management cost and I use the econometric estimate to measure the size of the waste haven effect. This methodology differs from previous studies.

In the pollution haven literature, the impact of environmental regulatory stringency on trade flows is estimated directly. This standard approach poses two empirical issues. First, the regulatory stringency variable suffers from endogeneity arising from omitted variables.[13] Regulation influences international trade through production costs. The omission of the other determinants of the cost results in biased estimates. Another source of endogeneity is simultaneity. Regulatory stringency is often chosen based on pollution emission or trade flows making it difficult to estimate the impact of stringency on such factors.

Recent studies use panel data methods to control for unobserved heterogeneity and use instrumental variables to challenge the simultaneity issues (Henderson and Millimet, 2007; Fredriksson, List, and Millimet, 2003; Kellenberg, 2009; Levinson and Taylor, 2008). In Chapter 1, I mitigate the omitted variable bias because I capture every determinant of waste treatment cost and not only its regulatory determinant. Simultaneity is less an issue since I look at the waste treatment cost difference and not at regulatory stringency differences.[14]

The last main difference with Kellenberg (2012) is the proxy of environmental regulatory strictness used. Though Kellenberg (2012) suggests the existence of a waste haven effect, it does not provide the size of the effect. This is because his measure of environmental regulatory stringency is a general composite index built using data from the 2003-2004 Global Competitiveness Report, a report based on survey responses of company executives who evaluate the stringency of air, water, chemical, and toxic waste regulations on a 1-7 scale.[15] Here, I not only test the waste haven hypothesis but I estimate the size of the effect.

[13]In the literature, this endogeneity issue is thought as being the source of the ambiguous effect of regulations on industry locations, foreign direct investment, and trade flows found in early pollution haven studies (Tobey, 1990; Jaffe, Peterson, Portney, and Stavins, 1995; Eskeland and Harrison, 2003).

[14]Government can influence regulations based on trade flows but they cannot influence every determinant of the waste treatment cost.

[15]Measuring environmental regulatory stringency is difficult. See Brunel and Levinson (2013) for a recent review of literature on measuring environmental regulatory stringency.

More precisely, the measure I employ here presents two principal advantages. First, I can quantify economic relationship because it is a cardinal measure. Second, this measure is not subject as many biases as other survey based measures. Levinson and Taylor (2008)find that Pollution Abatement Costs and Expenditure (PACE) have an economically significant effect on U.S. net imports. This statement is possible because PACE do have a quantitative meaning. On the other hand, factors other than regulations such as voluntary approach can impact the amount of PACE. General composite indexes are another way to measure stringency but they have magnitudes difficult to interpret and provide government officials or business managers' perception of the regulatory stringency.[16] Another benefit of the measure used here is that it concerns exclusively waste management activities whereas environmental regulation measures used in the literature are often too general or specific to other sector.[17]

In Chapter 1, I restrict the analysis on the European Union because of data availability. The European case is interesting because member states have different level of regulatory stringency. In particular, although many EU directives have been adopted to harmonize national waste regulation in Europe, the European Commission reports high variability between countries when assessing their waste management performance (BiPro, 2012). In some EU countries, no domestic legislation seeks to limit garbage dumps which represent sometimes more than 90% of total waste treatment.[18] In 2010, only three member states committed more than half of the 45 infractions to EU directives according to the EU commission. Considering the European case presents another benefit: data are available and comparable across countries.

Taking into account the endogeneity issue unveiled by Anderson and van Wincoop (2003) I apply country fixed effects when estimating a gravity equation. More specifically, the base model used consists in estimating a gravity equation using a Poisson Pseudo Maximum Likelihood estimator. This estimator allows for the consistent estimation of gravity models where zero is a frequent outcome of the dependent variable. I find that relative difference of

[16] It is difficult to tell what I actually learn about actual stringency from the perception of it (Kalamova and Johnstone, 2012).

[17] For instance, the lead content of gasoline.

[18] This figure concerns municipal solid waste.

10% in waste treatment costs between the two trading partners increases waste trade flow by around 8%. Using simulations, I find that waste tax changes can have an important impact on trade in waste. For instance, the model predicts that the abolishment of the Nowegian incineration tax in 2010 prevented 13 kilotons of waste to be exported from Norway to Sweden.

Waste recycling policies and trade in raw materials

Many public policies all over the world promote waste recycling. In the European Union, several directives established ambitious recovery rate targets for packaging, end-of-life vehicles and electronic waste in the 1990s. Japan adopted the so-called Fundamental Law for Establishing a Sound Material-Cycle Society (Junkangata Shakai) in 2000. China made a similar move in 2009 with the Circular Economy Promotion Law. In the United States, policies have mostly been implemented at state level (e.g. California, Illinois, Wisconsin, Oregon, and New York).

To achieve recycling targets, regulators have implemented subsidies, take-back obligations, landfill bans of recyclables, and so-called Extended Producer Responsibility Programs (EPR), by which the government makes producers responsible for collecting and recycling their products when they their reach end of life. Regulators have also introduced landfill and/or incineration taxes that indirectly promote recycling by increasing the cost of waste disposal. These policies have led to a waste recycling boom in many countries. As an illustration, the real annual growth rate of the metal recovery industry is a double digits figure in six European countries covered in the present paper. This trend also exists in developing countries. For instance, production of metallic secondary raw materials doubled every two years in China and Malaysia between 2002 and 2008.

Recycling policies have primarily been introduced for environmental reasons. As recycling is partly a substitute for waste disposal, its development reduces externalities generated by landfilling and incineration, in particular local soil, water and air pollution, methane, carbon dioxide and N2O.[19] The fact that recycled waste can substitute virgin raw materials brings additional benefits because the processing and use of virgin raw materials usually produces more pollution than waste recycling and recovery. Although recycling processes generate their own externalities, life cycle assessments of solid waste management systems show that recycling has an overall positive environmental benefit (Cleary, 2009).[20]

In recent years, policy makers have put more emphasis on the potential economic benefits of recycling. The success of concepts such as resource efficiency and circular economy signals that evolution. For instance, the flagship initiative of a resource-efficient Europe was introduced in 2011 by the European Commission as part of an overall strategy to generate growth and jobs. Among the economic arguments in favour of recycling, policy makers from countries or regions with limited exhaustible natural resources like Europe and Japan emphasize that recycling can reduce imports of raw material. As an illustration, the EU Steel Action Plan published in 2013 advocates increasing recycling, primarily on the grounds of reducing import dependency on raw materials (European Commission, 2002a).

To the best of my knowledge, Chapter 2 proposes the first empirical study on the impact of recycling on raw material imports. The most closely related work is a study on paper and lead by Van Beukering and Bouman (2001) who analyse the relationships between the international trade of recyclable materials, waste recovery and secondary material utilization rates. They address a different question, however: they seek to identify the determinants of recycling performance with trade of recyclables as one explanatory variable. Hence trade is on the right-hand side of their equation, whereas it is on the left-hand side in the present chapter. This difference highlights the concern of reverse causality between these variables because the recovery and trade of recyclable materials are simultaneously determined in the macroeconomic equilibrium. In Chapter 2, I devise an empirical strategy to control for this endogeneity bias.

Berglund and Söderholm (2003) make another cross-country econometric analysis of the

[19] See European Commission (2000) on the valuation of environmental externalities arising from waste disposal. See also Hu and Shy (2001) who document the health effects of waste incineration.

[20] In many cases, the economic cost of recycling is higher than the cost of waste disposal, particularly for household waste (EPA, 1994; European Commission, 2002b).

determinants of national recovery and utilization rates, but they do not consider trade as an independent variable. They find that recycling performance is mainly driven by non-policy country characteristics such as population density and urbanization rate. Other works look at trade of waste and secondary raw materials, without paying attention to the role of domestic activities in waste recovery. Grace, Turner, and Walter (1978) produced the first paper to analyse the international trade dimension of recyclables.

Several theoretical contributions also look at substitution between virgin raw materials and secondary raw materials, but without paying attention to trade issues. For example, Anderson and Spiegelman (1977) model substitution to investigate various policy options for the pulp and paper and steel industries. Di Vita (2007) develops an endogenous growth model to investigate how the degree of technical substitutability between virgin and secondary materials impacts the performance of the economy at an aggregate level.

Using a panel of 21 developed and developing countries from 1994-2008, Chapter 2 aims to measure the impact of metal scrap recovery on imports of metallic raw materials. I look at secondary material imports, and also at their virgin counterparts, because domestically produced secondary material can substitute virgin material. I deal with the endogeneity of metal recovery with exogenous country characteristics including population density, the level of education, and knowledge of environmental technologies. I also develop a strategy for controlling for the price volatility in raw material markets. I find that a 10% increase in metal recovery reduces imports of metallic raw materials by 3.3% in the base specification. These findings support the argument that waste policies contribute positively to the balance of trade.

Trade induced directed technical change

The second research axis of this dissertation investigates two mechanisms that play important roles in the PHE. In Chapter 3, I examine whether access to materials from low-cost countries reduces or increases firms' incentives to develop clean technologies.

They are different ways how trade openness could impact firms incentive to innovate.

First, higher trade openness could stimulate innovation because domestic firms face potentially higher competition from foreign firms. Several studies provide empirical evidence that firms operating in an industry where the degree of competition is high tend to be more innovative (Blundell, Griffith, and Van Reenen, 1995; Geroski, 1995; Nickell, 1996; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Aghion, Bechtold, Cassar, and Herz, 2014). Second, trade openness in the presence of assymetric environmental regulations could relocate not only production but also innovation.

In countries with strict environmental policies, firms have more incentive to reduce their emissions of pollutants. Companies have two strategies to comply with the regulations. First, they can innovate in clean technologies. Second, they can offshore a pollution intensive part of their production to countries with lower production costs. This second option becomes more profitable as trade costs get lower. Offshoring firms may have less incentive to innovate in general and especially in clean technologies. Nevertheless, offshoring may also change innovation behaviours in the sourcing countries.

The effectiveness of unilateral strict environmental innovation on net global green innovation may be undermined by international trade as it is the case for net CO2 emissions in a situation of carbon leakage. We can formulate several outcome resulting from the offshoring to low-cost countries under asymmetric environmental regulations. First, clean innovation is not induced anywhere and dirty innovations continue to prevail in both strict and lax countries. Second, clean innovation is induced in sourcing countries and not in the offshoring countries. We can coin this situation as a clean innovation leakage. Third, clean innovation is induced only in the offshoring countries and not in the sourcing countries. Finally, clean innovation is induced in both sourcing and offshoring countries. Which of these distinct outcome prevails is an empirical question.

Chapter 3 relates to two strands of the literature. First, it builds on the empirical literature on trade and technological change.[21] Previous studies have demonstrated that import competition, in particular from low-cost countries, has an influence on product innovation

[21] The theoretical literature on trade and technology is well developed and has been growing constantly since the seminal paper by Grossman and Helpman (1991).

(Bernard, Jensen, and Schott, 2006a; Iacovone, Rauch, and Winters, 2010; Lelarge and Nefussi, 2013). Bloom, Draca, and Reenen (2011) show that Chinese import competition has led to increases in R&D expenditures, patents and total factor productivity among European companies. Goldberg, Khandelwal, Pavcnik, and Topalova (2010) and Colantone and Crinó (2011) have shown that cheaper imported inputs boost firms' performance and lead to the introduction of new products. However, none of these papers consider the empirical effect of firms' *own* imports on their innovative activity. To the best of my knowledge, the only paper that uses this approach is Bøler, Moxnes, and Ulltveit-Moe (2012), which examines the interdependence of R&D and intermediate inputs and their joint impact on firm's productivity. Bøler, Moxnes, and Ulltveit-Moe (2012) find that importing increases productivity, which frees up resources that can then be used to increase innovation activity. Thus, trade affects the rate of technological change. In Chapter 3, I show that importing may also affect the *direction* of technological change by reducing incentives for environmentally-friendly innovation.

Second, Chapter 3 relates to the vast literature on the determinants of environmental innovation. Many studies have used patent data to measure clean innovation (Popp, 2002; Brunnermeier and Cohen, 2003; Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012), but an equally large number of papers have instead used data from the Community Innovation Survey (Horbach, 2008; Frondel, Horbach, and Rennings, 2008; Rennings and Rammer, 2011; Rennings and Rexhäuser, 2010; Rexhäuser and Rammer, 2011; Horbach and Rennings, 2012; Leeuwen and Mohnen, 2013; Veugelers, 2012). Most of the recent literature has focused on the impact of environmental policy on innovation (see e.g. Newell, Jaffe, and Stavins (1999), Popp (2002), Brunnermeier and Cohen (2003) and Johnstone, Haščič, and Popp (2010)).[22] No study has yet looked at trade with low-cost countries as a determinant of 'clean' innovation.

To investigate this question, I use theory to model jointly firms' trade and innovation behaviour. The theoretical model predicts that trade with low-cost countries has an ambiguous

[22]See Ghisetti and Pontoni (2015)'s meta-analysis for a comprehensive list of publications on the determinants of environmental innovation

effect on material or energy saving innovation. Under certain conditions, offshoring leads firms to undertake less material saving innovation. This is because firms can reduce their variable cost of production by importing cheap intermediate goods from low-cost countries. By doing so, they have less incentive to innovate in order to increase materials productivity and lower their production cost.[23]

To test this prediction and quantify this effect, I combine self-reported innovation data from the Community Innovation Survey with detailed firm- and product-level trade data for a sample of nearly 6,000 French companies observed from 1994 to 2010. Firm-level data allows us to control for (observed) firm heterogeneity, in particular whether the firm is also an exporter, is big, and has high productivity. I use industry fixed effects to take unobserved differences between industries into account.

I use product classification information to identify imported goods that enter into the production of energy-intensive products. These 'material' goods include for example metal products, pulp, and refined petroleum. Information on the country of origin of imports allows us to estimate the relative cost of inputs faced by companies. I complement this firm-level trade data with data on 'clean' innovation activities carried out specifically to reduce the use of these inputs.

I find strong evidence that a higher proportion of 'material' imports sourced from low-cost countries has a negative impact on firms' propensity to engage in 'clean' innovation. This finding is stable across various definitions of what can be considered a low-cost country and to the way I define 'material' imports. The magnitude of the effect is large: at the sample mean, an increase in the import share of 'material' products from India and China in a firm's total 'material' imports by one standard deviation (a move from 3% to 16%) is predicted to decrease firms' propensity to engage in environmental innovation by 15 percentage points. To put this figure into perspective, one can observe that the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010. Thus, the results suggest that, ceteris paribus, trade with low-cost countries might have significantly

[23]Because they both require firms to pay a fixed cost, import and innovation can become, at some point, mutually exclusive strategies to reduce variable cost of production.

reduced environmental innovation during the past 20 years.[24]

Chapter 3 focus on the two largest fast-growing developing economies, China and India, is motivated by three reasons. First, as illustrated above, these countries have played a growing role in providing companies in developed regions with cheaper intermediate goods in the last two decades, particularly in labour-intensive sectors. Second, the competition from these emerging economies has given rise to heated policy debates over the pertinence of introducing measures to protect domestic industries. A third, more data-driven reason is that the analysis showed that the results are unambiguously driven by China and India, although they are fully robust to considering other country groups such as BRICS countries (Brazil, Russia, South Africa, India and China) or low-wage countries.

Chapter 3 has important policy implications for the current debate on carbon 'leakage'. In a free-trade world, increased carbon prices following adoption of unilateral climate policies may generate a pollution-haven effect in other countries or regions, whereby foreign countries specialise in the production of carbon-intensive products in which they have a newly acquired competitive advantage and which they can subsequently export back to 'virtuous' countries. Environmental policies may thus fail to achieve their desired objective while destroying jobs in environmentally-friendly countries.[25] Chapter 3 suggests that leakage may not only affect jobs and emissions in the short run. It also affects long-run emissions and competitiveness by reducing incentives for firms to conduct innovation in 'clean' technologies. However, Chapter 3 does not provide an analysis on how offshoring impact innovation in low-cost countries. It is equally important to investigate this other aspect to measure the impact of asymmetric on net global clean innovation and long-run emission.

[24] Evidence suggests that, on the other side, competition from Chinese imports may have stimulated technical change in Europe (Bloom, Draca, and Reenen, 2011). Therefore trade might affect both the rate and the direction of technological change.

[25] Recent empirical papers show evidence of leakage, although this effect seems small (Levinson and Taylor, 2008). For example, Aldy and Pizer (2011) show that an increase in energy prices in the US following the introduction of a 15$/ton carbon tax would induce a domestic production decline of between 3 and 4 percent among energy-intensive sectors and a roughly 1 percent increase in imports.

Competitiveness impact of environmental regulations

In the last chapter, I use micro-data on French manufacturing to test a major part of the assumptions made in the seminal work of Porter and Van der Linde (1995). For the past twenty years, the Porter Hypothesis has been examined by a large number of papers (Ambec, Cohen, Elgie, and Lanoie, 2013; Dechezleprêtre and Sato, 2014). The results of these studies are highly mixed.[26] These studies vary from each other in a number of ways. First, some papers analyse regulations impact on productivity and other on profitability. Most of early studies employ country or industry-level data while recent studies tend to rely more on firm or plant-level data. Some papers analyse the effect of a specific policy while others use proxy of overall level of environmental regulation stringency. Finally previous papers do not all test the same assumptions implied by the Porter Hypothesis.

Chapter 4 makes several contributions. To the best of my knowledge, it is the first study to test jointly the different assumptions behind the Porter Hypothesis in a coherent framework. I identify five different hypotheses supported by the case studies exposed in Porter and Van der Linde (1995). First, environmental regulations trigger environmental innovation. This first hypothesis is called the "weak" version of the Porter Hypothesis in the literature (Jaffe and Palmer, 1997). Second, green innovation leads to higher productivity. Third, these regulation driven productivity gains partially or fully offset regulation compliance costs. Fourth, regulated firms develop a first mover advantage that makes them winners in the long run as foreign countries catch up with environmental regulations.[27] Fifth, Porter and Van der Linde (1995) stress that flexible policies such as market-based instruments have less adverse impact than command and control regulations on firm competitiveness. This last assumption is called "narrow" Porter Hypothesis by (Jaffe and Palmer, 1997).

Most studies analyse the overall effect of environmental regulations on productivity without analysing the role of green innovation nor testing for dynamic effects (Gollop and Roberts, 1983; Smith and Sims, 1985; Gray, 1987; Conrad and Morrison, 1989; Barbera and Mc-

[26] Ambec, Cohen, Elgie, and Lanoie (2013) provide several explanations for these variety of results in a recent literature review.

[27] I suggest that we call this assumption the "dynamic" Porter Hypothesis.

Connell, 1990; Dufour, Lanoie, and Patry, 1998; Boyd and McClelland, 1999; Berman and Bui, 2001; Alpay, Kerkvliet, and Buccola, 2002; Gray and Shadbegian, 2003; Greenstone, List, and Syverson, 2012; Tanaka, Yin, and Jefferson, 2014). Some papers test several hypothesis at a time but not altogether. Several studies incorporate dynamics but does not include the innovation dimension. For instance, Lanoie, Patry, and Lajeunesse (2008) and Albrizio, Koźluk, and Zipperer (2014) estimate distributed lag models and Rassier and Earnhart (2015) estimate the impact of current regulation on expected profitability. Other studies incorporate the innovation dimension but no dynamic effects (Lanoie, Laurent-Lucchetti, Johnstone, and Ambec, 2011; Rexhäuser and Rammer, 2014; Leeuwen and Mohnen, 2013).

Chapter 4 incorporates dynamics and distinguishes the effect of environmental regulations on the scale and the direction of innovation when testing the Porter Hypothesis. Although, it does not test the "narrow" Porter Hypothesis due to the proxy of environmental regulatory stringency used. As far as I know, Chapter 4 is the first to analyse the impact of environmental regulations on both productivity and profitability. This is important since profitability, which conditions firm employment and firm exit of a market, depends on productivity as well as regulations.

The second contribution of Chapter 4 lies in the empirical strategy. Regulators may impose less stringent regulations to protect firms with low Total Factor Productivity (TFP) or low profitability. If this is the case, then environmental regulations are endogenous. I deal with this simultaneity issue between firm productivity and environmental effort by employing an innovative way to generate an instrumental variable. Few studies actually deal with the endogeneity of environmental regulations. Gray and Shadbegian (2003) employ Arellano and Bond (1991)'s difference Generalized Method of Moments estimator to instrument pollution abatement operating cost with lagged independent variables. Greenstone, List, and Syverson (2012) build a contrefactual using plants in low pollution intensive industry as "control" group. Finally, Leeuwen and Mohnen (2013) use lagged independent variables.

Another advantage of the empirical strategy is the data sets used. Unlike more aggregated data, firm-level data allows for the identification strategy to be much less sensitive to macroeconomic shocks that are correlated with country or sector level innovation and environmental regulations. The data covers the entire manufacturing sector with few exceptions. Also the sizes of the data sets used ,up to 16,000 firms observed during 15 years, are important making hypothesis testing more reliable.

The third contribution of Chapter 4 is to test the impact of environmental regulations as a whole by using *both* environmental capital and operating costs as main independent variables. The advantage of these measure is that they summarize the multidimensionality of environmental regulations into measures comparable across firms producing in the same country. Studies focusing on a restricted set of policies cannot provide a general conclusion on the Porter Hypothesis. Moreover, identifying the effect of a specific policy poses empirical issues as one must account for other policies often correlated with the dependent variables and the policy of interest.

Using a two stage least square fixed-effects estimator on a panel data set I do not find that a higher share of capital expenditure dedicated to pollution abatement leads to lower firm TFP. Using a pooled data set, I find that firms having a higher share of capital expenditure dedicated to pollution abatement develop on average more green innovation. However, I find that the productivity return on R&D expenditure is lower as the share of green innovation increases. This result is new and the magnitude of the effect is far from being small. For instance, I find that an increase in R&D from 100,000 euros to 400,000 euros is predicted to increase TFP by 0.030 points if the share of green innovation is 25% and by 0.016 points if the share of green innovation is 50%.

Finally, I find that an increase in the share of environmental expenditure in a firm's total operating expenditure by one standard deviation (a move from 0.6% to 1.6%) is predicted to decrease the firm's profitability by 0.3 percentage points. The result regarding productivity is at odds with conventional economic wisdom. It is also evidence against the Porter Hypothesis. This is because environmental regulations cannot offset compliance operating costs if they do not lead to an increase in TFP.

In the end, it is important to stress that my Ph.D. thesis does not provide any conclusion on whether free trade is good or bad for the environment or more generally whether free trade is Pareto optimal or not. I like to think of this research as a contribution to the ongoing effort to understand the fascinating role of globalization in our societies and in our environment. Each chapter of the thesis consists in one research paper. I want to thank Sophie Bernard and Mouez Fodha for their useful feedbacks on Chapter 1. Chapter 2 is co-authored on equal basis with Matthieu Glachant. Finally, Chapter 3 is co-authored on equal basis with Antoine Dechezleprêtre, David Hemous, and Mirabelle Muûls.

Quantifying the impact of asymmetric waste taxes on hazardous waste trade within the European Union

Damien Dussaux

MINES ParisTech, PSL - Research University, CERNA - Center for industrial economics

Abstract

International trade in waste has been growing very rapidly in the last decade. Many fear that this trend is driven by cross-country differences in the environmental stringency of waste policies, creating waste havens in laxer countries. These concerns are based on a two inter-related arguments: waste as an input tends to flow in countries with lower management costs and management costs in the waste sector are strongly influenced by environmental regulations. Using pooled data of 27 European countries for year 2008 and 2010, we estimate that a difference of 1 percent between the unit costs of two trading partners increases waste flows by around 0.8 percent. These findings allow us to simulate the impact of waste tax changes on trade in waste.

Keywords: Hazardous Waste, Pollution Haven, Environmental policy

JEL Classification: F18, F64, Q53, Q56

Chapter 1

Quantifying the impact of asymmetric waste taxes on hazardous waste trade within the European Union

1.1 Introduction

International waste trade has been growing rapidly during the last decade. The average annual growth rate of 6% from 2002 to 2010 and at least 5.8 million tons of waste crossed a border in 2010.[1] Many fear that this trend is driven by cross-country differences in environmental regulation, creating so-called "waste havens" in countries with laxer waste policies.[2] The term "waste haven effect" comes from the term "pollution haven effect" which is widely used in the trade and environment economic literature to indicate that lax environmental regulations in some countries are a source of comparative advantage in pollution intensive goods production.

These concerns have been reinforced by the publicity given to cases such as the 2006 Ivory Coast toxic waste dump offloaded by the ship Probo Koala, causing the death of 17

[1] These figures are for legal trade in waste only.

[2] The term waste haven includes every pollution emitted from waste management activities and is not restricted to waste accumulation.

inhabitants in Abidjan. They are based on consistent arguments: waste is an input for disposal and material recovery activities and economic theory predicts that inputs tend to flow in countries with lower production costs, and environmental regulation undoubtedly exerts a strong influence on waste management costs. Trading waste potentially improves welfare as it makes possible to locate waste disposal and recovery activities where it is cheaper to do so. However, it is socially detrimental if there is a waste haven effect that is if the importing country's comparative advantage stems from insufficient internalization of environmental and health costs. In this paper, we develop an empirical analysis to estimate the waste haven effect using pooled data of 27 European countries for year 2008 and 2010.[3]

The European case is interesting because member states have different level of regulatory stringency. In particular, although many EU directives have been adopted to harmonize national waste regulation in Europe, the European Commission reports high variability between countries when assessing their waste management performance (BiPro, 2012). In some EU countries, no domestic legislation seeks to limit garbage dumps which represent sometimes more than 90% of total waste treatment.[4] In 2010, only three member states committed more than half of the 45 infractions to EU directives according to the EU commission. Considering the European case presents another benefit: data are available and comparable across countries. Here, we consider waste that are "unprocessed" in the sense that they have not been landfilled, incinerated or recovered yet. In contrast, secondary raw materials produced by waste recovery are processed waste used as inputs in the manufacturing sector. Actually, these commodities obey to very different industrial logics and the impact of environmental regulations on waste processing is much more important than its impact on secondary raw material utilization.

In this paper, we proceed in two stages to quantify the waste haven effect. First, we estimate econometrically how much waste management costs differences influence trade flows. In the second stage, we simulate the impact of waste taxes on waste management cost and we use our econometric estimate to measure the size of the waste haven effect. Our methodology

[3]Our sample includes Norway and every EU member states except Greece and Malta.
[4]This figure concerns municipal solid waste.

differs from previous studies. In the pollution haven literature, the impact of environmental regulatory stringency on trade flows is estimated directly. This standard approach poses two empirical issues. First, the regulatory stringency variable suffers from endogeneity arising from omitted variables.[5] Regulation influences international trade through production costs. The omission of the other determinants of the cost results in biased estimates. Another source of endogeneity is simultaneity. Regulatory stringency is often chosen based on pollution emission or trade flows making it difficult to estimate the impact of stringency on such factors. Recent studies use panel data methods to control for unobserved heterogeneity and use instrumental variables to challenge the simultaneity issues (Henderson and Millimet, 2007; Fredriksson, List, and Millimet, 2003; Kellenberg, 2009; Levinson and Taylor, 2008). In this paper, we drastically cut the omitted variable bias because we capture every determinant of waste treatment cost and not only its regulatory determinant. Simultaneity is not an issue since we look directly at the waste treatment cost difference.

The other main empirical issue is that measuring environmental regulatory stringency is difficult.[6] Here, we not only test the waste haven hypothesis but we estimate the size of the effect. This is possible because we use hard data. More precisely, our measure presents two principal advantages. First, we can quantify economic relationship because it is a cardinal measure. Second, our measure is not subject as many biases as other survey based measures. Levinson and Taylor (2008)find that Pollution Abatement Costs and Expenditure (PACE) have an economically significant effect on U.S. net imports. This statement is possible because PACE do have a quantitative meaning. On the other hand, PACE data are based on business managers' answers to very difficult questions. It is extremely complicated to identify investment or expenditure motivated solely by environmental regulations from investment and expenditure motivated by other factors.[7] General composite indexes are

[5]In the literature, this endogeneity issue is thought as being the source of the ambiguous effect of regulations on industry locations, foreign direct investment, and trade flows found in early pollution haven studies (Tobey, 1990; Jaffe, Peterson, Portney, and Stavins, 1995; Eskeland and Harrison, 2003).

[6]See Brunel and Levinson (2013) for a recent review of literature on measuring environmental regulatory stringency.

[7]Suppose a firm makes an investment that reduces both production cost and pollution emissions. The firm may have invested even in the absence of regulation. If this is the case, reporting this investment as compliance cost overestimates stringency.

another way to measure stringency but they have magnitudes difficult to interpret and provide government officials or business managers' perception of the regulatory stringency.[8] Another benefit of our measure is that we focus exclusively on waste management activities whereas environmental regulation measures used in the literature are often too general or specific to other sector.[9]

A recent paper by Kellenberg (2012) is the only work which deals with the question addressed in the present paper, that is, the impact of domestic environmental legislation on international trade of waste.[10] Others either examine domestic trade within the US (Levinson, 1999a,b; Deyle and Bretschneider, 1995), or they deal with international trade, but consider the influence of other variables such as the participation in the Basel Convention (Kellenberg and Levinson, 2013) or income per capita (Baggs, 2009). Our work differs from Kellenberg (2012) in many ways. Kellenberg (2012) pools unprocessed waste and secondary raw material in his estimations. He estimates directly the impact of cross-country difference in regulatory stringency on bilateral waste flows. Though his work suggests the existence of a waste haven effect, it does not provide the size of the effect. This is because his measure of environmental regulatory stringency is a general composite index built using data from the 2003-2004 Global Competitiveness Report, a report based on survey responses of company executives who evaluate the stringency of air, water, chemical, and toxic waste regulations on a 1-7 scale.

Taking into account the endogeneity issue unveiled by Anderson and van Wincoop (2003) we apply country fixed effects when estimating a gravity equation. More specifically, our base model consists in estimating a gravity equation using a Poisson Pseudo Maximum Likelihood estimator. We find that relative difference of 1% in waste treatment costs between the two trading partners increases waste trade flow by around 0.8%. Using simulations, we also find

[8] It is difficult to tell what we actually learn about actual stringency from the perception of it (Kalamova and Johnstone, 2012).

[9] For instance, the lead content of gasoline.

[10] It is also worth mentioning a few theoretical works such as Kohn (1995) or, more recently Kinnaman and Yokoo (2011) and Bernard (2011) who focus on some very specific waste trade (used electronic goods). They confirm the result of Copeland (1991) who shows that restrictions on trade such as those in the Basel Convention can improve welfare in the presence of illegal disposal of waste.

that waste tax changes can have an important impact on trade in waste.

The paper is organized as follows. The next section discusses the distinction between unprocessed waste and secondary raw materials and the impact of environmental regulation on unprocessed wastes trade. Section 3 presents the data, namely bilateral trade flows and waste management costs. Section 4 develops the empirical methods. Section 5 gives the results along with robustness checks. In section 6, we run simulations on the impact of waste tax changes on waste trade. The last section concludes.

1.2 Conceptual framework

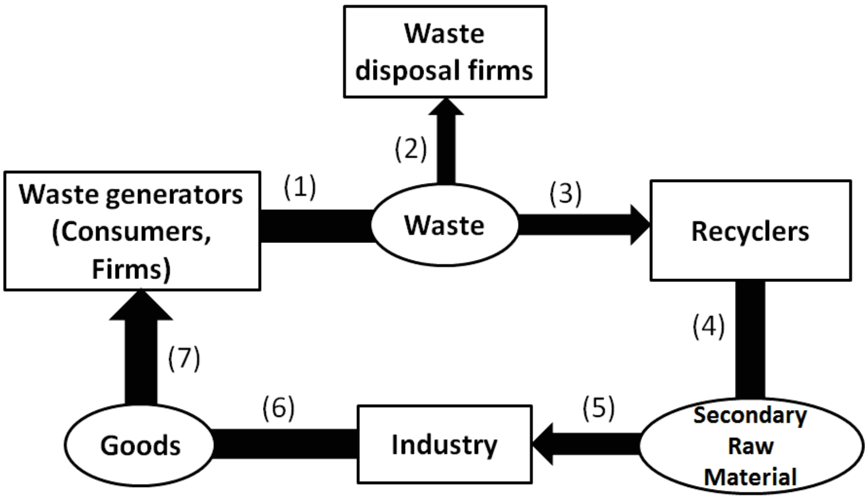
How waste flows in the economy is depicted in Figure 1-1. Households' consumption and firms' production generate waste in (1). Waste are either collected separately or mixed. Collected waste can then be domestically incinerated (with or without energy recovery), landfilled in (2) or recovered (3 & 4). Recyclers perform waste recovery in (3) and (4), the action to transform waste into secondary raw material. These materials can then be used into industrial production, an activity that is called utilization (5). As illustrated, recycling consists both in waste recovery and secondary raw material utilization.[11] Final goods are produced by the industry (6) and purchased by households and firms (7).

In a two countries world, a waste owner that seeks to dispose of his waste has thus four options: domestic disposal (2), domestic recovery (3), and foreign disposal (2) or recovery (3) through export. How does the waste generator choose among these different options? The owner objective is to minimize its costs. To do so, he compares the total cost of the four options. In both domestic and foreign markets, he first compares the cost of disposal and the cost of recovery and identifies the least costly option. If the cost of the domestic least costly option exceeds the sum of the cost of the least costly foreign option and trading cost, then the waste owner chooses to export his waste abroad.

In this paper, we exclude secondary raw material and focus on unprocessed waste trade.

[11] This distinction now appears clearly in the new structural classifications such as the International Standard Industrial Classification of All Economic Activities (ISIC Rev.4) and Statistical classification of economic activities in the European Community (NACE Rev.2).

Figure 1-1: The structure of waste flows



Unprocessed waste are waste that have not been through step (2) or step (3) pictured in Figure 1-1.[12] This is because the environmental issues are more important for waste management activities than for secondary raw material utilization. Secondary raw materials are used in regulated pollution intensive industries such as the steel and the paper industries but their utilization can be motivated by environmental policies that promote recycling. On the contrary, the impact of environmental regulation stringency has, in theory, a clear impact on waste management. By the mean of standards or economic instruments, regulations increase dramatically the cost of waste management. Countries with lax environmental policies fail to internalize the external effects generated by waste recovery, incineration, and landfilling. This source of comparative advantage in waste management favors waste imports from stricter countries. In the end, trade allows strict countries to export pollution directly to lax countries. Landfill and incineration taxes are among the regulatory instruments that impact the most waste management cost. Rates of these taxes vary importantly across the European Countries (see Table 5 in the appendix). These cross-country differences in waste taxes may explain waste trade. The objective of this paper is to quantify the impact of waste tax changes on trade in waste.

[12]Baggs (2009) focuses exclusively on hazardous wastes that are unprocessed while Kellenberg (2012)'s dependent variable is a mix of secondary raw material and unprocessed waste.

To do so, we build a new methodological approach. Instead of looking directly at the impact of regulation on trade, our methodology is built upon the choice of the waste owner described above. We estimate the effect of cost on waste trade flows because this is what drives waste trade flows in theory. In contrast, estimating the impact of environmental regulatory stringency directly on trade in waste poses serious empirical issues. The first main problem is the endogeneity of the environmental regulatory stringency due to omitted variables. To estimate the proper impact of regulation strictness, one should control for every other determinants of waste management costs: technology, non-environmental taxes, capital and labor cost. Failing to control for these determinants indubitably yields biased estimate of the effect of regulatory stringency since it is likely correlated with these determinants.

We adopt an approach that is also less sensitive to another empirical issue: simultaneity. Governments choose or revise environmental regulation stringency based on factors that are influenced by stringency. To estimate properly the effect of regulation of these factors, researchers resort to natural experiment or instrument variable estimation.[13] The major difficulty with these approaches is that both natural experiments and valid instrument variable candidates are rarely available. Simultaneity is less an issue here because governments do not choose waste management cost based on trade flows. They can influence the cost only through regulations but the other cost determinants such as capital and labor costs are not influenced by waste trade flows.

Our method allows us to circumvent another issue: measuring regulatory stringency is extremely difficult (Brunel and Levinson, 2013). A first difficulty is the multidimensional aspect of regulation. There are several economic instruments or standard different depending on the waste category, the plant location, and the plant environmental performance. Summarizing the entire environmental regulation stringency regarding waste by landfill and incineration taxes is insufficient. The literature on environmental regulation and competitiveness overcame the multidimensionality issue by looking at the outcome of environmental

[13] Henderson (1996) uses a natural experiment to investigate the effect of ground-level ozone regulation on economic activity in the U.S. See Millimet and Roy (2011) for a review of research using instrumental variables for stringency.

regulation such as pollution abatement and control cost. This poses other issues well described in Brunel and Levinson (2013).

Here, we acknowledge that waste regulatory stringency cannot be well summarized into a single measure. Instead, we propose a new attractive tool. Provided we know the impacts of the different regulations on the unit waste disposal cost, our model can be used to show how much regulations actually impact trade in wastes.

1.3 Data

1.3.1 Bilateral Waste Trade Flows

Our dependent variable is the bilateral annual trade flows of waste. More simply, it is the total of unprocessed wastes shipped from country i to country j for every country pair ij. Data are available for 27 European countries for year 2008 and year 2010.[14] This means a total of 1,404 observations.[15] Data come from the United Nations Comtrade database that contains comprehensive data on trade flows for commodities classified under the Harmonized Commodity Description and Coding System (HS) developed by the World Customs Organization (WCO). UN Comtrade data come either directly from countries or from organizations like OECD and FAO. By checking detailed data and total data, the UN Department of Economic and Social Affairs (2011) advocates that UN Comtrade data are of higher quality than other data sources.

We select HS commodity codes that unambiguously define the commodity as an unprocessed waste. The term 'secondary raw material' is absent in the Harmonized Commodity Description and Coding System (HS) developed by the World Customs Organization (WCO). Rather, both waste and secondary raw material are regrouped under the term 'waste and scrap'. However, the nomenclature gives enough information to assume that certain commodities are likely unprocessed wastes and that others are likely secondary raw material

[14] See country list in Table 1.3.

[15] There are 27 x 26 = 702 country pairs over 2 years that is 702 x 2 = 1,404 observations.

(recovered wastes).[16] From their description in the nomenclature, we classify every 'waste and scrap' commodity as unprocessed waste or secondary raw material (see Table 6 and Table 7 of the appendix).[17] It is difficult to assert with certainty whether the commodities that we identified as secondary raw material incorporate only secondary raw material. For instance, it would be possible that some ferrous waste and scrap requires further recovery once arrived in the recipient country. We cannot exclude that workers in developing countries sort and process barehanded these commodities in poor environmental and safety conditions. Thus, we only assume that these commodities are mainly composed of secondary raw material. It is important to note that we measure only legal waste shipment. In reality, there are also illegal waste shipments and they are difficult to measure.

We do not include nuclear wastes and electronic waste in our aggregate dependent variable. Radioactive wastes flows are not addressed in this paper because nuclear waste management is a specific issue that is highly political and would require another proper analysis. Electronic wastes are not included because it is a particular waste category which disposal is forbidden within the EU.[18] Disposal cost differences should not affect electronic waste trade flows the way it affects the other unprocessed wastes trade flows. In fact, it depends on member state compliance to the directive and their ability to enforce it. Consider two different cases. First, assume that every member states successfully enforce the interdiction. In that case, disposal cost differences play no role in determining electronic waste trade flows. Second, assume that no member state actually enforces the interdiction. In that case, disposal cost differences do influence electronic trade flows. These two extreme cases are very unlikely. Instead, it is more likely that that some member states successfully enforce the regulation and some not. In this situation, it is not possible to disentangle the regulation compliance effect from the cost difference effect on electronic wastes trade flows. Here,

[16] For instance, the commodities regrouped under the HS codes '7204 - ferrous waste and scrap; remelting scrap ingots of iron or steel' and 'Waste, parings & scrap, of polymers of ethylene' are most likely to be secondary raw material whereas the commodities '300680 – Waste pharmaceuticals' and '382510 – Municipal waste' fall under the unprocessed waste category.

[17] Most commodities we identified as being unprocessed waste are actually qualified as hazardous waste in Baggs (2009).

[18] Article 14 of the directive 2006/66/EC of the European Parliament and of the Council of 6 September 2006.

by not including dropping electronic waste trade flows, we avoid the contamination of the aggregate trade flows of unprocessed wastes.

To measure trade flow from country i to country j, one can use import data reported by country j or export data reported by country i. Our dependent variable is defined as the maximum between the import data and the export data. The reason is that export data and import data are not given the same reliability. Import data are generally considered to be more reliable than export data because customs offices have to verify customs duties and import tax while recording imported goods. Also, because they raise controversy, waste trade flows could suffer from underreporting. Our methodology takes this possible bias into account. More precisely, we calculate the maximum weight value of the two mirroring statistics at the HS 6-digit level taking full advantage of the detailed provided by the nomenclature and then sum these maxima to calculate our aggregate dependent variable. One benefit of this method is to limit drastically the number of false zeroes. Figure -8 of the appendix shows global waste traded over 2002 and 2010 measured with import data, export data, and the maximum data. Our methodology allows us capturing 50% of the waste trade that would be otherwise categorized as zero.

We consider quantity traded to be of higher interest than the value traded because some wastes can have null or negative value for their owners. Low value of trade flows may hide big quantity of waste traded. The low sample correlation between the quantity and the value of waste trade flows supports our intuition.[19] Kellenberg (2012) also uses the quantity to build his dependent variable. His argument is that the quantity of waste is more proportional to environmental damages than the value of waste.

Data show that the total quantity of unprocessed wastes exchanged in 2010 between the 27 countries of our sample corresponds to 2.1 million tons. This top world trading block represent 37% of the total quantity of wasted traded globally. Table 1.1 shows the top bilateral flows in our sample averaged over 2008 and 2010. Countries like Norway, Sweden, the Netherlands and Belgium play a significant role in EU waste trade. The top trading pairs

[19] The correlation between quantity and value flows is 0.9 for secondary raw material while it is only 0.5 for unprocessed waste.

share a common characteristic: they all consist in neighboring countries. Transport cost must play an important role in determining unprocessed waste trade. This is not surprising given that these commodities have generally a low unit value.

Table 1.1: Highest sample trading pairs

#	Country pairs	Quantity traded (Kilotons)	Sample share
1	Norway -> Sweden	155	10.80%
2	Netherlands -> Belgium	119	8.30%
3	Netherlands -> United Kingdom	107	7.40%
4	Denmark -> Norway	99	6.90%
5	Italy -> Spain	95	6.60%
6	Germany -> Belgium	89	6.20%
7	Sweden -> Norway	88	6.10%
8	France -> Belgium	77	5.40%
9	Belgium -> Germany	74	5.10%
10	Netherlands -> Germany	53	3.70%
Total top ten		**954**	**66.60%**

Average quantity traded based on 2008 and 2010 UN Comtrade data.

BiPro (2012) suggests that the level of environmental regulatory stringency differ importantly across EU countries. Do strict EU countries export waste to laxer EU member states? To answer that, we use the waste management performance score calculated by BiPro (2012) to classify countries in two groups.[20] We define as Group H the group of countries that have a score higher than the median score and group L the group of countries with a score lower than the median . The waste management score is calculated based on several criteria reflecting the main legal requirements of the EU waste regulations. These criteria include: compliance with the waste management hierarchy, application of economic instruments to support the waste hierarchy, quality of the waste treatment facilities, waste diversion targets compliance, number of court cases and infringement, et cetera. Table 1.2 contains the quantity of unprocessed waste traded for the four possibilities of country pairs: from H country to other H country, from H country to L country, from L country to other L country, and from L country to H country.

[20]See Table 8.

Column 2 of Table 1.2 shows the total quantity of unprocessed waste traded by flow type. Column 3 shows the average quantity of unprocessed waste traded per country pair and column 4 reports the standard deviation. Table 1.2 is composed of 3 panels. Panel (1) shows trade flows for all countries, panel (2) for non-contiguous countries, and panel (3) for contiguous countries. From panel (1) we see that countries with high waste management score do export wastes towards low score countries but the converse is also true. Low score countries even export three times more waste towards high score countries. That does not mean that the waste haven effect do not exist or is small. Panel (1) also shows that 85% of unprocessed waste trade takes place between H countries. This may be due to the bigger economic size of H countries compared to L countries.[21] The second column shows that the quantity of unprocessed waste exchanged varies a lot between country pairs and this is true whether the origin or the destination is H or L. The second and third panels of suggest that transport cost have an impact on trade in waste. The average annual quantity shipped is substantially higher when the two trading partners are contiguous countries.

1.3.2 Measuring Unit Waste Management Costs

As explained in Section 1.2 our first aim is to estimate the relationship between waste management cost difference and trade in unprocessed waste. To calculate the relative difference in unit waste management cost between a country i and a country j, we use the following formula:

$$CostDiff_{ijt} = \ln[Min(UC_{Dit}, UC_{Rit}] - \ln[Min(UC_{Djt}, UC_{Rjt}] \tag{1.1}$$

Where UC_{Dit} denotes the unit disposal cost in country i at year t and UC_{Rjt} is the unit recovery in country i at year t. The formula reflects the fact that a firm compares the cheapest domestic option with the cheapest foreign option as explained in Section 1.2). Our formula enables to measure relative difference between bilateral pairs. This is a better measure than the absolute difference between unit costs that does not take into account the difference

[21] Based on World Bank data, we find that the average annual GDP of H countries is almost three times the average annual GDP of L countries.

Table 1.2: Annual unprocessed waste flows between 27 European countries

	Total flow (kilotons)	Average flow (tons)	(Std. Dev.)
(1)			
All	1,428	2,344	(4,222)
H to H	1,219	7,866	(12,646)
H to L	49	295	(534)
L to H	153	955	(1,744)
L to L	7	57	(104)
(2) Non contiguous			
All	504	930	(1,720)
H to H	350	2,825	(4,882)
H to L	16	105	(190)
L to H	136	902	(1,671)
L to L	1	9	(16)
(3) Contiguous			
All	925	13,597	(19,035)
H to H	869	28,029	(31,288)
H to L	33	3,275	(4,194)
L to H	17	1,842	(2,584)
L to L	6	354	(547)

The average quantity traded is based on 2008 and 2010 UN Comtrade data.
H is the group of countries with high waste management performance score.

between country-pairs that have small unit cost and country-pairs that have big unit cost. In our analysis, we calculate the unit disposal cost using the following formula:

$$UC_{Dit} = \frac{Cost_{Dit}}{Quantity_{Dit}} \tag{1.2}$$

where $Cost_{Dit}$ is the waste disposal total cost in country i at year t and $Quantity_{Dit}$ is the total amount of wastes going to domestic disposal in country i at year t. We proxy $Cost_{Dit}$ by the turnover of the 382 – Waste treatment and disposal group defined under the statistical classification of economic activities in the European Community (NACE Rev. 2).[22] This

[22]NACE Rev. 2 is equivalent to the International Standard Industrial Classification (ISIC) rev. 4.

group encompasses incineration activities, landfill operations and other waste treatments.[23] Data come from Eurostat Structural business statistics (SBS) database and are available for 27 European countries from 2008 to 2011.

Data on waste quantity come from Eurostat Waste generation and treatment database and are available for 30 European countries for 2004, 2006, 2008, and 2010. The advantage of these data is that it gives the quantity of waste treated for each operation: incineration with energy recovery, recovery other than energy recovery, incineration without energy recovery, and disposal (deposit onto or into land, land treatment and release into water bodies).[24] Accordingly to the definition of industry 382, our denominator is equal to the sum of waste quantity treated across operations except the quantity classified under the "recovery other than energy recover" operation. By definition, UC_{Dit} represents the average unit cost of disposal in country i. Similarly, we calculate the unit recovery cost using the following formula:

$$UC_{Rit} = \frac{Cost_{Rit}}{Quantity_{Rit}} \tag{1.3}$$

where $Cost_{Rit}$ is the waste recovery total cost in country i at year t and $Quantity_{Rit}$ is the amount of wastes recovered locally by country i at year t. We proxy $Cost_{Rit}$ by the turnover of industry 38.32 – recovery of sorted materials class defined under the NACE . Accordingly with the definition of class 38.32, $Quantity_{Rit}$ corresponds to the quantity of recyclable wastes that are actually recovered. Data come from the Eurostat Waste generation and treatment database. The recyclable wastes include ferrous and non-ferrous metallic wastes, glass wastes, paper and carboard wastes, rubber wastes, plastic wastes, wood wastes, and textile wastes.

The proxies of the unit management costs we use have nevertheless two drawbacks. The first drawback is that we cannot use fixed effect estimator that would allow us to control fully for country pairs unobserved heterogeneity because we have countries waste treatment quantities for only two years. The other issue is that we are unable to attribute a NACE class to some of the operations classified under the "recovery other than energy recover"

[23]Details are available in Table 10 of the appendix.
[24]Details are available in Table 11 of the appendix.

category such as solvent reclamation/regeneration, regeneration of acids or bases, recovery of components used for pollution abatement, recovery of components from catalysts. As a result, the denominators used to calculate the unit costs may be slightly underestimated.

According to the data, the average unit waste disposal cost is 43 EUR/t and the average unit recovery cost is 520 EUR/t. In Table 1.3, we report the average unit disposal cost and the average unit recovery cost for each of the 27 countries.[25] These figures are consistent with the idea that recovering waste is more costly than incineration or landfilling. From equation (1.1), the relative difference in unit waste management cost equals the logged difference of the unit disposal costs because disposal is less costly than recovery for every country of our sample. Denmark and Belgium have the highest disposal unit costs with 175 and 170 EUR/t respectively whereas Romania and Bulgaria have the lowest unit costs with 0.5 and 0.3 EUR/t respectively. The distribution of the unit disposal cost is positively skewed with 19 of the 27 countries having a unit disposal cost lower than 50 EUR/t.

Some statistics presented in the table 1.3 are not in line with expectations. For instance, the cost is similar in Latvia and the United Kingdom. Our perception is that environmental regulations are more stringent in the United Kingdom than in Latvia so we expect a higher cost in the former country. Luxembourg and Sweden, for which we expect high waste management cost, are located at the bottom of the table. These examples of inconsistency might be due to waste heterogeneity. To compute the waste management unit costs, we use the total quantity of waste as the denominator. This total quantity is a mix of different types of waste going from chemical waste to electronic waste. We do that because data of the numerator (the total cost of waste management) is only available for all unprocessed waste as an aggregate.

The formula used here is a weighted average of each waste category's unit cost. For each category, the weight is the share of the total quantity of waste treated. Consequently even if two countries have the same unit costs for each waste categories, the outcome of the formula will be different if the countries' composition in the waste categories is not the same. Table 12 of the appendix illustrates this point. This can explain why the unit disposal

[25] These figures are averaged between 2008 and 2010.

cost computed for Sweden is low. Using Eurostat data, one can find that 56% of the total quantity of waste eliminated in Sweden in 2010 is wood waste going to incineration. The second more frequent treatment is disposal of chemical waste with 8.6% of the total quantity of waste eliminated. As a result, the unit disposal cost is actually close to the incineration cost of wood waste which is not costly in Sweden. This is because Sweden generates energy with almost all waste incinerated and has plants with high energy yield.

The formula used in this paper corresponds to the best that we can do given availability of country level waste data. We find a positive although small correlation, equal to 0.37, between unit disposal cost and the waste management performance score defined above. An analysis at the waste category level would be much more appropriate but is not feasible at the moment. Descriptive statistics are given in Table 1.4. Data on GDP are expressed in Purchasing Power Parity constant 2005 international dollars come from the World Bank. Gravity variables come from CEPII.

Table 1.3: Waste management cost in 27 European countries (euros per ton)

Rank	Country	Unit disposal cost	Unit recovery cost
1	Denmark	175	323
2	Belgium	170	712
3	Italy	116	366
4	Norway	77	559
5	Germany	71	360
6	Czech Republic	71	430
7	Ireland	57	1768
8	Netherlands	51	281
9	Hungary	49	206
10	Austria	44	140
11	Spain	41	163
12	France	39	511
13	Portugal	36	268
14	Slovak Republic	28	202
15	United Kingdom	28	407
16	Latvia	24	1765
17	Slovenia	20	252
18	Poland	14	151
19	Lithuania	13	496
20	Finland	8	947
21	Cyprus	7	819
22	Croatia	6	1389
23	Sweden	4	451
24	Luxembourg	3	17
25	Estonia	2	168
26	Romania	0.5	645
27	Bulgaria	0.3	256

These figures are averages on 2008 and 2010.

Table 1.4: descriptive statistics for the unprocessed waste analysis

Variables	Obs.	Mean	Std. Dev.	Min	Max
Dependent variables					
Bilateral 'unprocessed' waste flow (kilograms)	1,219	2.34E+06	1.45E+07	0	2.80E+08
Independent variables					
Waste management cost difference	1,219	-0.079	2.396	-6.668	6.668
Log (Exporter's GDP)	1,219	26.113	1.334	23.767	28.653
Log (Importer's GDP)	1,219	26.148	1.387	23.767	28.653
Log (Distance)	1,219	6.987	0.639	4.903	8.235
Contiguity	1,219	0.112	0.315	0	1
Common official language	1,219	0.031	0.174	0	1
Colonial ties	1,219	0.030	0.169	0	1

1.4 Empirical method

1.4.1 A model based on the gravity equation

To estimate the impact of waste management cost difference on unprocessed waste trade flows, we extend the standard gravity equation to the following:

$$W_{ijt} = \alpha_0 Y_{it}^{\beta_1} Y_{jt}^{\beta_2} Diff_{ijt}^{\beta_3} \prod_{k=4}^{K} \delta_{kij}^{\beta_k} \tag{1.4}$$

where W_{ijt} is the total quantity of unprocessed wastes that flow from country i to country j, Y_{it} is the GDP of country i, Y_{jt} is the GDP of country j, $Diff_{ijt}$ denotes the bilateral waste disposal cost absolute difference, and δ_{kij} denotes time-invariant bilateral characteristics such as distance, contiguity, colonial ties and common language.

The gravity equation come from Tinbergen et al. (1962) which made the analogy between international trade and the gravitation force. As in Newton's law of universal gravitation, the force/trade is proportional to the mass/size of the two entities/economies whereas it is inversely proportional to the distance that separates them. GDP is generally used as a proxy of the size of an economy and the distance proxies mainly transportation costs. This basic gravity equation conforts the intuition behind trade in waste. The size of the exporting economy should have a positive effect on bilateral trade since the bigger the economy the more it produces waste and have to recover or eliminate. As a result, there are more wastes in the recovery, disposal and exporting channels. This argument is also made by Baggs (2009) who argues that the size of the importing economy should likewise have a positive effect on bilateral trade because larger economies can afford the substantial investment needed to develop more disposal capacity. The simple scatter plots of GDP over the total amount of waste imported (Figure 4 in the appendix) and exported (Figure 5) are in line with these assumptions. The corresponding correlations suggest that exporter and importer GDPs are good candidate to control for a scale effect in trade in waste. The other advantage in using the gravity equation is that it allows controlling for numerous trade costs.

In our estimation, we also control for the potential effect of EU membership on trade costs by including a Regional Trade Agreement dummy equal to 1 when both countries are in the same custom union or participate in a Free Trade Agreement. This is important since previous literature indicates that Preferential Trading Agreements can have a significant impact on bilateral trade costs. For example, Baier and Bergstrand (2007) provide empirical evidence that free trade agreements increase member's international trade. Here, a positive effect on bilateral trade is expected because EU membership grants the access to the EU common market in which member states encounter low or no trade barriers. However, because of its extremely low variability, the RTA dummy is omitted to prevent multicollinearity.[26]

Eventually, we apply exporter and importer fixed effects to our pooled estimation following Anderson and van Wincoop (2003). This allows controlling for any time-invariant specific exporter and importer heterogeneity that may be correlated with the dependent variable and with the independent variables. This reduces drastically the endogeneity of the regressors included in the estimated equation. We also include a set of time dummies to reduce further endogeneity issue. Any exogenous factor that may impact every country pairs is controlled for.

It is important to notify the existence of potential omitted variables. To begin with, some countries such as Sweden heavily relies on waste incineration for heat generation. It means that factors such as the energy demand impacts the quantity of waste imported. Consequently, our main coefficient of interest could be biased if the energy demand is correlated with unit disposal cost. Here, we assume that this correlation is not high for two main reasons. First, not all country have incineration as a large part of their energy supply. Second, energy demand could influence incineration cost through economics of scale. A higher demand will be met with a larger production which might reduce the unit cost of incineration. This effect depends on countries' plant capacity. Given a capacity, it might be not possible to fully exploit economics of scale. As we assume treatment capacity are captured by country dummies, the correlation between energy demand and unit disposal cost conditional on

[26] The only countries that are not part of the EU custom union before 2013 is Croatia that joined the EU on July 1st 2013 and Norway participates in a FTA with the EU since 1973.

country dummies is likely to be low.

Another potential omitted variable is third countries effect. For instance, it is likely that an increase in the French waste tax will influence trade between Italy and Germany. Recent development in spatial econometrics allows to control for such third effect. Unfortunately, these methodologies requires a much larger amount of degrees of freedom. In particular, most control variables have to be interacted with the inverse distance matrix (Baltagi, Egger, and Pfaffermayr, 2007). Here, we do not have enough observations to carry out such methodology as inference would be out of reach.

1.4.2 Pooled Poisson Pseudo Maximum Likelihood Estimator

We use the Pseudo Poisson Maximum Likelihood (PPML) estimator proposed by Santos Silva and Tenreyro (2006) to estimate equation (5):

$$W_{ijt} = exp(\beta_1 \log(Y_{it}) + \beta_2 \log(Y_{jt}) + \beta_3 CostDiff_{ijt} + \sum_k \beta_k \delta_{kij} + \sum_t \alpha_t \gamma_t + \sum_i \theta_i \omega_i + \sum_j \theta_j \omega_j) + u_{ijt} \tag{1.5}$$

Where γ_t are the t time dummies, ω_i is exporter i dummy, and ω_j is importer j dummy. For consistent estimation, we assume that the countries dummies are successful at capturing factor endowments both related to cost and trade such as infrastructure. This is because our sample is composed of two close years 2008 and 2010 during which factor endowments have likely been of similar importance.

We do favor this nonlinear estimator for several reasons. Santos Silva and Tenreyro (2006) with cross section data and Westerlund and Wilhelmsson (2006) with panel data showed that log-linearization model to estimate gravity equation presents two major drawbacks. First, it provides biased and inefficient estimates in the presence of heteroskedasticity that is inherent in the log-linear model. Secondly, the log transformation of the dependent variable leads to truncate the sample by dropping zero values of bilateral trade. This can be problematic as the number of observations decreases sometimes dramatically.[27] For those cases, it makes

[27] The proportion of zero value for our dependent variable is 55.5%.

the linear regression estimation unsuitable. Based on Monte Carlo simulations, Santos Silva and Tenreyro (2006) demonstrate that the PPML estimator performs better than OLS under several different patterns of heteroskedasticity in Monte Carlo simulations. This estimator is also favored by Kellenberg (2012) to estimate the gravity equation.

Consistently, as our dependent variable takes only non-negative integers, we assume it follows a Poisson distribution with probability in equation (1.6).[28]

$$Pr(W_{ijt}) = \frac{e^{-\lambda_{ijt}} \lambda_{ijt}^{W_{ijt}}}{W_{ijt}!} \tag{1.6}$$

where λ_{ijt} is the parameter of the Poisson distribution. We make this assumption because using a Poisson model makes possible to preserve zero values in our sample as $W_{ijt} = 0$ is a natural result of the Poisson distribution as shown by Westerlund and Wilhelmsson (2006). In addition, we use a sandwich variance estimator clustered over the country pairs. This is because our dependent variable suffers unambiguously from over-dispersion (see Table 1.4) implying that the Poisson variance assumption does not hold. Thus the standard errors need to be properly adjusted to obtain consistent estimates in our Quasi-Maximum Likelihood Estimation.[29]

We also employ a Zero Inflated Poisson Pseudo-Maximum Likelihood (ZIPPML) estimator as an alternative estimator to the PPML. The ZIPPML estimator presents the benefit to estimate the probability of no trade in a first stage called inflate equation. Such a method is appropriate when the dependent variable contains a high share of zero which is 56% in our case. In such a case, alternative estimator such as the Negative Binomial estimator performs badly because it cannot disentangle over-dispersion coming from extreme value and over-dispersion coming from an excessive number of zeroes (Greene, 2005). Zero Inflated Poisson (ZIP) models introduced by Lambert (1992) are found to perform better.

[28] It poses no econometric problem if the dependent variable is continuous.

[29] Quasi-Maximum likelihood is a class of estimation where the Poisson variance assumption is relaxed.

1.5 Regression results

1.5.1 Main results

We report the main results in Table 1.5. Our base estimation is reported in column (1). We find that waste management cost difference has a significant impact on unprocessed waste trade at the 5% level. The coefficient equals 0.826 meaning that a 1% decline in the importing country's unit disposal cost relative to a bilateral partner is predicted to increase the quantity of waste imported by this country by 0.8%. This effect can be illustrated using country pairs in our sample. Germany exported to Slovak Republic about 428 kilotons of waste in 2008 and 3.5 kilotons of waste in 2010. While the unit cost in Slovak Republic had become 3.3 times bigger, from 13 to 43 USD/t, the unit disposal cost in Germany had increased by 7%, from 69 to 74 USD/t. As a result, the ratio between the two countries decreased by 68%. This decline in the ratio explained a 56% reduction in exports. Convergence in unit disposal costs prevented ceteris paribus the export of 239 kilotons of waste from Germany to the Slovak Republic. A similar analysis shows that the 17% increase in the unit cost ratio between Belgium and Italy from 2008 to 2010 intensified exports by 14%. Relative variations in unit disposal costs were therefore responsible for 6.3 kilotons of the additional exports of waste from Belgium to Italy.

As expected, distance has a large impact on trade in waste. It is not astonishing because 'unprocessed' waste commodities have low unit value. Contiguity has not a significant effect. The negative sign of its coefficient is somewhat surprising since we expect contiguity to facilitate the connection between trading partner transport networks easing waste trade. Considering our European sample, it is likely that the distance captures bilateral transport costs more accurately and sufficiently. Our results show that sharing the same official language facilitates trade in waste. In every model, bilateral economic size has an expected positive but not significant effect on waste export. It is not surprising since the numerous country dummies already capture country size.

There is no particular reason that the cost difference effect described here does not exist between countries that are not in our sample. The advantage of our sample is that it contains countries that differ importantly from one another. For example, countries' development levels, economic size, and industrial composition vary greatly. For 2008, the standard deviation for GDP per capita is 12 thousand USD which is about Latvia's income per capita and slightly more than Romania's and Bulgaria's.

In column (2), we report the estimated coefficients and standard errors when using ZIPPML estimator. The coefficient for the cost difference is highly similar to the one obtained using PPML and statistically significant. The coefficient found in the 1st stage probit equation (denoted inflate) are consistent with our expectation. The probability to engage in trade in waste lowers with distance and increases when the two trading partners are contiguous and share a common official language.

1.5.2 Robustness checks

In Table 1.6, we estimate the unprocessed waste trade gravity equation while dropping potential outlying countries. Table 9 shows the top importers and exporters of unprocessed waste in our sample for 2008 and 2010. The Netherlands and Germany are major waste exporters far from the other countries. To verify that our results are not driven by these potential outliers, we drop the Netherlands in column (1) and the Netherlands and Germany in column (2). In column(3) and (4), we do the same with the large importers, dropping subsequently Belgium and Germany. We find that the impact of relative difference on unit waste disposal cost is of a magnitude similar to the complete sample. In column (5), we drop the largest trading country pair: Norway and Sweden and find a significant but lower coefficient. In column (6), we drop Bulgaria and Romania because they have very small unit disposal costs compared to the other countries and we find that the coefficient remains almost unchanged. Because it is the only country outside the European custom union and it has the highest export/GDP ratio, we drop Norway in column (7). The coefficient found is still significant but slightly lower. Since it has the smallest import/GDP ratio, we run the regression in column (8) without Estonia and find a coefficient of a magnitude similar to the complete sample coefficient.

Additional robustness checks are performed in Table 13 of the appendix. In column (1), we report our base estimation for readability reason. In column (2), electronic waste flows are included in the dependent variable. The cost difference effect remains statistically significant but the coefficient is a little lower than the base estimate. In column (3), only import statistics are used to build our dependent variable. We do find a slightly higher coefficient. Finally, we use trade data from Eurostat in column (4) and we find a coefficient of similar size.

Table 1.5: Waste disposal cost difference and bilateral trade of unprocessed trade

	Dependent variable Quantity of unprocessed waste exported from i to j		
	PPML	ZIPPML	Inflate
	(1)	(2)	
Waste management cost difference	0.826**	0.826**	-0.309
	(0.321)	(0.323)	(0.273)
Log (Exporter's GDP)	1.165	1.545	1.770
	(5.568)	(5.883)	(2.999)
Log (Importer's GDP)	4.248	3.992	-6.424**
	(6.364)	(6.555)	(2.600)
Log (Distance)	-2.666***	-2.451***	2.271***
	(0.379)	(0.376)	(0.291)
Contiguity	-0.0889	-0.0928	-1.055**
	(0.332)	(0.328)	(0.493)
Common official language	1.563***	1.557***	-28.16***
	(0.485)	(0.501)	(1.178)
Colonial ties	0.438	0.582	-0.790
	(0.814)	(0.938)	(0.824)
Observations	1,219	1,219	
Country pairs	658	658	
Exporter and Importer Fixed-Effects	yes	yes	
Time dummies	yes	yes	
Log Likelihood	-1.41E+09	-1.32E+09	
Pseudo R-squared	0.84		

Clustered standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All columns include a constant not reported for clarity.
Waste management cost difference is the difference between logged unit disposal cost.

Table 1.6: Waste disposal cost difference and bilateral trade of unprocessed trade

	Dependent variable: quantity of unprocessed waste exported from i to j							
	NLD dropped (1)	NLD & GER dropped (2)	BEL dropped (3)	BEL & GER dropped (4)	NOR <-> SWE dropped (5)	ROM & BGR dropped (6)	NOR dropped (7)	EST dropped (8)
Waste management cost	0.753*	0.911**	0.849**	1.152***	0.606**	0.824**	0.681**	0.800***
difference	(0.423)	(0.397)	(0.404)	(0.322)	(0.291)	(0.320)	(0.269)	(0.307)
Log (Exporter's GDP)	0.445	1.008	3.305	4.383	-5.406	1.408	-1.749	2.464
	(5.330)	(6.852)	(4.706)	(5.948)	(5.175)	(5.625)	(3.573)	(5.598)
Log (Importer's GDP)	2.049	3.536	7.285	6.494	(3.033	4.31	-4.944	7.966
	(5.785)	(7.870)	(6.909)	(7.886)	(5.453)	(6.481)	(5.545)	(7.701)
Log (Distance)	-3.178***	-3.384***	-3.151***	-4.195***	-2.621***	-2.662***	-1.966***	-2.636***
	(0.468)	(0.367)	(0.388)	(0.477)	(0.382)	(0.381)	(0.396)	(0.380)
Contiguity	-0.202	1.338*	-0.241	1.113*	-0.686*	-0.093	-0.071	-0.132
	(0.382)	(0.699)	(0.361)	(0.649)	(0.408)	(0.332)	(0.490)	(0.333)
Common official language	1.294***	3.216***	0.758	-1.070	2.414***	1.563***	2.261***	1.578***
	(0.485)	(0.606)	(0.823)	(1.756)	(0.466)	(0.486)	(0.481)	(0.503)
Colonial ties	0.690	-3.102**	0.716	-0.908	2.164***	0.438	1.992***	0.659
	(0.677)	(1.419)	(0.721)	(1.326)	(0.426)	(0.826)	(0.417)	(0.876)
Observations	1,125	1,035	1,125	1,035	1,215	1,023	1,119	1,123
Country pairs	609	562	609	562	656	556	606	608
Exporter and Importer FE	yes	yes	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes	yes	yes
Log Likelihood	-850e+06	-434e+06	-1090e+06	-476e+06	-1190e+06	-1390e+06	-1010e+06	-1380e+06
Pseudo R-squared	0.88	0.92	0.84	0.91	0.84	0.84	0.84	0.84

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include a constant not reported for clarity.
Waste management cost difference is the difference between logged unit disposal cost.

1.6 Quantifying the impact of waste tax changes on waste trade

In this section, we measure the impact of regulatory changes on waste trade. In a first step, we model the impact of regulatory changes within a country on domestic waste management cost. In a second step, we include the resulting waste management cost in our previous econometric model to estimate changes in waste flows between the countries that change their environmental regulation level and their trade partners. We do that by considering several policy scenarios.

1.6.1 A simple model of the market for waste disposal

An issue when simulating tax scenarios is that a variation in the tax rate may drive a change in the share of waste handled by the different disposal activities. For instance, increasing a landfill tax while the incineration tax remains constant reduces landfilling and increases incineration. Because the cost of incineration differs from the cost of landfilling, one must account for the effect of the tax on the composition of waste diposal to compute the unit disposal cost of the new equilibrium.

To predict how a tax redirects waste flows between the two disposal options, we develop a simple analytical model. Recall that Q_{Di} denotes the quantity of waste sent to disposal in country i. A quantity of waste Q_{Ii} is incinerated and a quantity of waste Q_{Li} is landfilled so that $Q_{Di} = Q_{Ii} + Q_{Li}$. Incineration cost and landfilling costs are assumed to be quadratic so that the marginal costs c_L and c_I are linear:

$$c_L = a_L Q_L \tag{1.7}$$

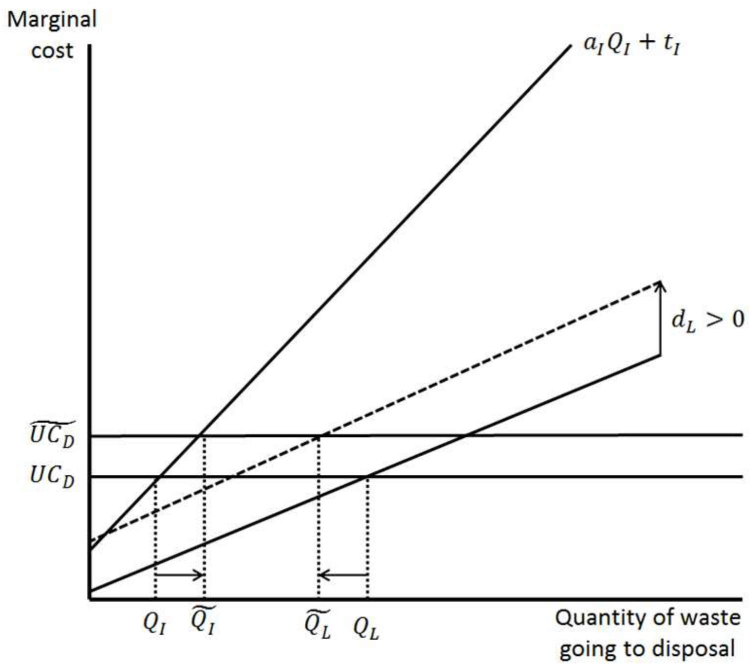
$$c_I = a_I Q_I \tag{1.8}$$

where we suppress the country subscript for clarity and $a_L > 0$ and $a_I > 0$. Suppose there exists a landfill tax of which rate is t_L and an incineration tax of which rate is t_I. Assuming that the market for waste disposal in country i is perfectly competitive:

$$a_L Q_L + t_L = a_I Q_I + t_I \tag{1.9}$$

That is, the sum of the marginal cost and the tax rate is equal across waste disposal options. From equation (1.2) and (1.9), we can show that the unit disposal cost UC_D is also equal to the sum of the two marginal costs weighted by their share in the waste quantity handled. $UC_D = \frac{Cost_D t}{Q_D} = \frac{(a_L Q_L + t_L)Q_L + (a_I Q_I + t_I)Q_I}{Q_L + Q_I} = (a_L Q_L + t_L)\alpha + (a_I Q_I + t_I)(1-\alpha)$ where α is the share of the total waste quantity going to landfill. Figure 2 illustrates the equilibrium.

Figure 1-2: Landfill tax and price of waste disposal



Consider now an increase of d_L of the landfill tax rate. Assuming that the demand for waste disposal is inelastic, that is Q_D remains constant if the price of disposal changes, what is the new allocation of Q_D between landfilling and incineration?[30] Ex post, total marginal

[30]The inelastic demand for waste treatment is not a very strong assumption since waste owners must dispose of their wastes.

costs are again equal so that equation (1.9) becomes

$$a_L\tilde{Q}_L + t_L + d_L = a_I\tilde{Q}_I + t_I \tag{1.10}$$

where $\tilde{Q}_L$ is the new quantity of waste going to landfill and $\tilde{Q}_I$ is the new quantity of waste going to incineration. From equation (1.10), it is apparent that the new quantity landfilled is:

$$\tilde{Q}_L = \frac{a_I Q_D + t_I - (t_L + d_L)}{a_L + a_I} \tag{1.11}$$

which is consistently decreasing in the level of the landfill tax change. At equilibrium, the new unit disposal cost $\tilde{UC}_D$ must be equal to the sum of the marginal cost of landfilling and the new landfill tax rate so that:

$$\tilde{UC}_D = a_L\tilde{Q}_L + (t_L + d_L) \tag{1.12}$$

Substituting 1.11 in 1.12, we obtain the new unit cost of disposal:

$$\tilde{UC}_D = a_L \frac{a_I Q_D + t_I - (t_L + d_L)}{a_L + a_I} + (t_L + d_L) \tag{1.13}$$

The increase in the landfill tax raises the unit disposal cost because we assume that a_L and a_I are strictly positive.[31] The increase in the unit disposal cost due to an increase of d_I of the incineration tax rate can be derived by symmetry.

1.6.2 Introduction of a landfill tax in Czech Republic and Lithuania

In this sub-section, we derive the impact of waste tax change on waste trade flows with two simple but policy relevant scenarios. Both Czech Republic and Lithuania governments are considering the introduction of a landfill tax. It is interesting to know how waste trade flows would be impacted by these regulatory changes.

Among the 5 million tons going to domestic disposal in Czech Republic in 2010, 84% were

[31] The derivative is $\frac{\partial \tilde{UC}_D}{\partial d_L} = \frac{a_I}{a_L + a_I} > 0$.

landfilled and 16% were incinerated for a total cost of 357 million euros.[32] The unit disposal cost is equal to 71 € per ton and Czech Republic is planning a 60 € per ton landfill tax for 2015. We use the equality between the unit disposal cost, the marginal cost of landfilling, and the marginal cost of incineration to derive a_L and a_I for the Czech Republic. Using equation (1.13) we find that the tax increases the unit disposal cost by 50 € per ton. With the tax, landfilling represents now 72% of the total quantity going to disposal. Assuming that disposal costs remain the same in the other countries and using the econometric estimate obtained in section 5, this disposal cost change increases the waste exports of Czech Republic towards the other countries by 58% and decreases its waste imports by 34%. Table 1.7 gives the resulting net export increases towards Czech Republic's trade partners. Net exports towards Germany would rise by 1.5 kilotons, imports from the United Kingdom would fall by 40 tons, and exports towards Slovakia would increase by 132 tons. Eventually, the tax would cause a 67% increase in Czech Republic's waste net export.[33]

Lithuania currently plans to introduce a landfill tax at 22 € per ton. Using the previous method, this would raise the unit disposal cost from 16 € per ton to 37 € per ton. This increase in the unit disposal cost would result in a 159% increase in Lithuania's waste net export. The resulting net export increases towards Lithuania's trade partners are given in Table 1.7.

[32]Data on the quantity of waste handled by each operation come from Eurostat.

[33]It is worth to note that we take into account the impact of trade quantity of waste treated locally in Czech Republic and thus on the unit treatment cost. The results presented correspond to the final equilibrium.

Table 1.7: landfill tax and net export increase towards the trade partners of Czech Republic and Lithuania

Czech Republic introduces a landfill tax of 60 €/t				**Lithuania introduces a landfill tax of 22 €/t**			
Partner	Net export increase	Partner	Net export increase	Partner	Net export increase	Partner	Net export increase
Austria	< 1	Lithuania	< 1	Austria	0	Latvia	310
Belgium	1	Luxembourg	< 1	Belgium	0	Luxembourg	0
Bulgaria	< 1	Netherlands	2	Bulgaria	0	Netherlands	1,300
Croatia	< 1	Norway	0	Croatia	0	Norway	3
Denmark	2,000	Poland	108	Czech Rep.	< 1	Poland	1,600
Estonia	0	Portugal	0	Denmark	0	Portugal	0
Finland	0	Romania	7	Estonia	< 1	Romania	0
France	1	Slovakia	132	Finland	0	Slovakia	0
Germany	1,500	Slovenia	0	France	0	Slovenia	0
Hungary	0	Spain	< 1	Germany	54	Spain	0
Ireland	0	Sweden	2	Hungary	0	Sweden	0
Italy	< 1	United Kingdom	40	Ireland	0	United Kingdom	0
Latvia	0	**Total**	**3,790**	Italy	< 1	**Total**	**3,310**

These figures are in tons based on 2010 trade flows.

1.6.3 Removal of a tax on incineration

In this section we consider another policy scenario but this time we look at change in the rate of the incineration tax. On October 1st 2010, both Norway and Sweden repealed their incineration tax. An interesting policy question is what would have Norway waste trade flows been if the tax remained in force? Our model can help us to build a counterfactual where only Sweden removes the incineration tax. With the tax at 13 € per ton, the Norwegian unit disposal cost would have been 94 € per ton instead of 90 € per ton. The tax withdrawal increased domestic landfilling by 0.5%, raised Norway's import by 3% and decreased Norway's export by 3%. Table 1.8 gives the net export of waste prevented by the abolishment of the Norwegian incineration tax by trade partners. By removing the tax, Norway prevented 12.7 kilotons of waste to be exported towards Sweden.

Table 1.8: Incineration tax and net waste export of Norway by trade partners

Partner	Net export prevented	Partner	Net export prevented
Austria	0	Latvia	0
Belgium	0	Lithuania	0
Bulgaria	0	Luxembourg	0
Croatia	0	Netherlands	6
Czech Rep.	0	Poland	0
Denmark	4,171	Portugal	0
Estonia	0	Romania	0
Finland	76	Slovak Rep.	0
France	15	Slovenia	0
Germany	1,825	Spain	0
Hungary	0	Sweden	12,675
Ireland	0	United Kingdom	147
Italy	7	**Total**	**18,923**

In this section, we showed that the introduction of landfill and incineration taxes can have an important impact on trade flows. A rise in environmental regulation may take the form of the introduction of landfill or incineration tax but also in the introduction of tax on pollution emission or emission standards. Any of these policies would increase the unit disposal cost and impact bilateral trade in waste and pollution emission levels. In fact, if the impact of a particular measure on the unit waste disposal cost is known, then our econometric model can tell how the measure actually impacts trade in waste.

1.7 Conclusion and discussion

Our work provides empirical evidence of the waste haven effect. We stress the importance of distinguishing unprocessed waste from secondary raw materials because they are not driven by the same factors. We rely on a covariate of interest based on hard data that allows us to control for every determinants of waste trade. Using pooled data composed by 27 European countries for 2008 and 2010, we can quantify the impact of cost difference on trade in waste. It is found that a difference of 10% between management costs of two trading partners increases the waste trade weight by around 8%. This large effect suggests that waste regulatory stringency have a big impact on trade in waste.

Here, the main contribution lies in the fact that provided the impact of a particular policy measure on the unit waste disposal cost is known, our approach can be used to show how the measure actually impacts trade in wastes. This makes it an attractive tool for policy makers. In this paper, we run simulations to quantify the impact of waste taxes changes on trade in waste. These changes can have big impact on waste trade. We find that the introduction of a landfill tax equal to € per ton in Czech Republic would increase its net export by 67%. We also find that Lithuania's net export increases by 159% due to the introduction of a landfill tax equal to 22 € per ton. In contrast, we find that the removal of the Norwegian incineration tax equal to 13 € per ton only decreases Norway's export by 3%.

This work could be extended in several directions. First, the identification strategy would strongly benefit from the use of fixed-effect estimators. This would require data on waste quantity to be available for additional years. Second, our simple policy simulation only allows for the introduction of economic instruments such as taxes. In fact, the waste regulations are more complex because they include numerous instruments such as ban et cetera. Further studies could estimate the impact of different policy instruments on the unit waste disposal cost and use our trade model to compute the effect of these policies on bilateral waste trade. Third, our sample contains only European member states. Given that waste regulations in developing countries are significantly laxer than European regulations, our estimate can be seen as a lower bound of the global waste haven effect. Adding developing countries while controlling for regulations that forbid the flows of hazardous waste from non OECD countries to OECD countries would yield a more accurate estimate of the global waste haven effect.

How much does recycling reduce imports? Evidence from metallic raw materials

Damien Dussaux and Matthieu Glachant

Abstract

In countries with limited exhaustible natural resources, reducing imports of raw materials is increasingly viewed as a significant side benefit of waste recycling. Using a panel of 21 developed and developing countries from 1994-2008, we seek to measure the size of this benefit by estimating the impact of metal scrap recovery on imports of metallic raw materials. We deal with the endogeneity of metal recovery with exogenous country characteristics including population density, the level of education, and knowledge of environmental technologies. We also develop a strategy for controlling for the price volatility in raw material markets. We find that increasing metal recovery by 10% reduces imports of metallic raw materials by 3.3% in our base specification. This result confirms that waste policies that favor recycling may have a sizeable impact on the balance of trade.

Keywords: raw materials, trade, waste recovery, recycling, metal, input substitution

JEL Classification: F18, L61, Q53

Chapter 2

How much does recycling reduce imports? Evidence from metallic raw materials

2.1 Introduction

Many public policies all over the world promote waste recycling. In the European Union, several directives established ambitious recovery rate targets for packaging, end-of-life vehicles and electronic waste in the 1990s. Japan adopted the so-called Fundamental Law for Establishing a Sound Material-Cycle Society (Junkangata Shakai) in 2000. China made a similar move in 2009 with the Circular Economy Promotion Law. In the United States, policies have mostly been implemented at state level (e.g. California, Illinois, Wisconsin, Oregon, and New York). To achieve recycling targets, regulators have implemented subsidies, take-back obligations, landfill bans of recyclables, and so-called Extended Producer Responsibility Programs (EPR), by which the government makes producers responsible for collecting and recycling their products when they reach end of life. Regulators have also introduced landfill and/or incineration taxes that indirectly promote recycling by increasing the cost of waste disposal. These policies have led to a waste recycling boom in many countries. As an illustration, the real annual growth rate of the metal recovery industry is in double digits in six European countries covered in the present paper. Production doubled every two years in China and Malaysia between 2002 and 2008.

Recycling policies have primarily been introduced for environmental reasons. As recycling is partly a substitute for waste disposal, its development reduces externalities generated by landfilling and incineration, in particular local soil, water and air pollution, methane, carbon dioxide and N2O.[1] The fact that recycled waste can substitute virgin raw materials brings additional benefits because the processing and use of virgin raw materials usually produces more pollution than waste recycling and recovery. Although recycling processes generate their own externalities, life cycle assessments of solid waste management systems show that recycling has an overall positive environmental benefit (Cleary, 2009).[2]

In recent years, policy makers have put more emphasis on the potential economic benefits of recycling. The success of concepts such as resource efficiency and circular economy signals that evolution. For instance, the flagship initiative of a resource-efficient Europe was introduced in 2011 by the European Commission as part of an overall strategy to generate growth and jobs.

Among the economic arguments in favor of recycling, policy makers from countries or regions with limited exhaustible natural resources like Europe and Japan emphasize that recycling can reduce imports of raw material. As an illustration, the EU Steel Action Plan published in 2013 advocates increasing recycling, primarily on the grounds of reducing import dependency on raw materials (European Commission, 2002a). Using a panel of 21 developed and developing countries from 1994-2008, this paper aims to measure the size of this benefit by estimating the impact of metal scrap recovery on imports of metallic raw materials. We look at secondary material imports, and also at their virgin counterparts,

[1]See European Commission (2000) on the valuation of environmental externalities arising from waste disposal. See also Hu and Shy (2001) who document the health effects of waste incineration.

[2]In many cases, the economic cost of recycling is higher than the cost of waste disposal, particularly for household waste (EPA, 1994; European Commission, 2002b). The net social benefit of recycling is thus a priori unclear. This question has been much less explored in literature. A recent study by Kinnaman, Shinkuma, and Yamamoto (2014) however shows that recycling rates are higher than the socially optimal rates in Japan.

because domestically produced secondary material can substitute virgin material. We deal with the endogeneity of metal recovery with exogenous country characteristics including population density, the level of education, and knowledge of environmental technologies. We also develop a strategy for controlling for the price volatility in raw material markets. We find that a 10% increase in metal recovery reduces imports of metallic raw materials by 3.3% in our base specification. These findings support the argument that waste policies contribute to improving the balance of trade.

To the best of our knowledge, this paper proposes the first empirical study on the impact of recycling on raw material imports. The most closely related work is a study on paper and lead by Van Beukering and Bouman (2001) who analyze the relationships between the international trade of recyclable materials, waste recovery and secondary material utilization rates. They address a different question, however: they seek to identify the determinants of recycling performance with trade of recyclates as one explanatory variable. Hence trade is on the right-hand side of their equation, whereas it is on the left-hand side in the present paper. This difference highlights the concern of reverse causality between these variables because the recovery and trade of recyclable materials are simultaneously determined in the macroeconomic equilibrium. They do not address this issue while we devise an empirical strategy to control for endogeneity biases. Berglund and Söderholm (2003) make another cross-country econometric analysis of the determinants of national recovery and utilization rates, but they not consider trade as an independent variable. They find that recycling performance is mainly driven by non-policy country characteristics such as population density and urbanization rate.

Other works look at trade of waste and secondary raw materials, without paying attention to the role of domestic activities in waste recovery. Grace, Turner, and Walter (1978) produced the first paper to analyze the international trade dimension of recyclates. More recently, Kellenberg (2012) examined whether cross-country differences in environmental policy stringency was driving waste towards the laxest countries.

Several theoretical contributions also look at substitution between virgin raw materials and secondary raw materials, but without paying attention to trade issues. For example, Anderson and Spiegelman (1977) model substitution to investigate various policy options for the pulp and paper and steel industries. Di Vita (2007) develops an endogenous growth model to investigate how the degree of technical substitutability between virgin and secondary materials impacts the performance of the economy at an aggregate level.

The remainder of our paper proceeds as follows. Section 2.2 describes the empirical approach used to quantify the impact of metal recovery on metallic raw materials imports. In Section 2.3, we present the data and provide some descriptive statistics. Estimation results are presented in Section 2.4. We also perform several robustness checks. Section 2.5 discusses the results and concludes.

2.2 Empirical approach

2.2.1 Analytical framework

Waste recycling involves two steps. The first is waste recovery, which consists in collecting and processing recyclable waste in order to obtain secondary raw materials. In the second step, secondary raw materials such as ferrous scrap are used to produce new goods. In many industries, these can substitute virgin raw materials. As a result, all other things being equal, an increase in the supply of secondary raw materials is expected to diminish the demand for virgin materials. However, the technical substitutability between secondary and virgin metallic materials is not perfect (Radetzki and Van Duyne, 1985; Blomberg and Hellmer, 2000) For instance, several final products made of high-quality metal require inputs with a high percentage of purity. Several grades of secondary raw metal result from waste metal recovery. The lowest purity grades cannot be used in the production of complex metal products.

Estimating the impact of metal recovery on imports of metallic raw materials thus requires taking into account three industries that center around metal commodities. The first is the basic metal manufacturing industry, which inputs metallic raw materials such as iron ores to produce finished or semi-finished metal products such as crude steel or steel sheets. Metallic raw materials in this case come from two different upstream industries: the mining industry, which supplies virgin material, and the recovery industry, which collects and processes recyclable waste into secondary raw materials.

Material suppliers can be located at home or abroad. Our research question amounts to investigating the degree of substitutability between two sources of material inputs in basic metal manufacturing: imported raw materials (both virgin and secondary) and secondary materials produced on the domestic market. Econometrically, this involves regressing the volume of imports of raw materials to the size of waste recovery activities in the country. A consistent econometric analysis of the relationship between these two variables then requires controlling for two other factors: demand (captured by the size of the domestic basic metal manufacturing industry) and the size of the domestic mining industry supplying virgin materials that potentially compete with raw material imports.

Formally, we thus write the total import value of metallic raw materials ($import$) as a function of the domestic production value of secondary metals ($recovery$), the domestic production value of virgin metals ($mining$), and the domestic production value of the basic metal industry ($demand$) to proxy the demand for metallic raw materials:

$$import = F(recovery, mining, demand) \tag{2.1}$$

Assuming that imported metallic raw materials, domestic secondary metals, and domestic virgin metals are (imperfect) substitutes for the production of basic metals, we expect a negative relationship between $import$ and $recovery$ as well as between $import$ and $mining$. We also expect that $import$ increases with $demand$.

2.2.2 Econometric specification

A log linear specification of (2.1) that can be estimated with panel data is:

$$\begin{aligned} Log(import_{it}) =& \alpha_0 + \alpha_1 Log(recovery_{it}) + \alpha_2 Log(mining_{it}) + \alpha_3 Log(demand_{it}) + \\ & \alpha_4 Log(GDP/capita_{it}) + \alpha_5 tariff_{it} + \delta_i + \gamma_t + u_{it} \end{aligned} \tag{2.2}$$

where indices i and t indicate country and year, respectively. In comparison with (2.1), we essentially add control variables.[3] δ_i are country fixed effects that control for any time invariant factors that may affect imports of metallic raw materials and may be correlated with other regressors. For instance, remote countries tend to import less than others. γ_t are year dummies that control for any time-varying factors such as variations in global industrial output or energy price changes that impact every country. We also include (the log of) GDP per capita to control for wealth effects. $tariff_{it}$ is a variable measuring the level of potential import barriers. Following standard practice in trade literature, we take the average of effective tariffs that apply specifically to imports of metal raw materials. We give more detail on this variable in the Data section. Finally, u_{it} is the error term that includes unobserved heterogeneity that varies over time and across countries.

2.2.3 Identification issues

For a given level of domestic metallic raw materials consumption, it is safe to assume that the variables *import* , *recovery*, and *mining* are simultaneously determined: they are macroeconomic aggregates which result from choices made simultaneously by numerous local and foreign economic agents in the concerned industries, which decide how much raw material to produce and consume. As a result, recovery, and mining are likely to be endogenous in (2.2).

To solve this problem, we employ a General Method of Moments Instrumental Variable (GMM - IV) estimator to get an unbiased estimate of α_1. In our base specification, we

[3]Note that this functional form does not allow for the inclusion of a country that does not produce metal ore.

use two instrumental variables to identify the equation: the log of population density *Log* (*popdens*), and the level of education measured by the percentage of tertiary enrollment (*education*). As a robustness check, we use an additional instrumental variable, which is the country's level of knowledge of environmental technologies.[4]

We judge that *Log* (*popdens*) is a valid instrument for *recovery* because it does not directly influence raw material imports once total demand for metallic raw material controlled for whereas we expect that densely populated countries are more inclined to develop waste recovery. In densely populated areas, waste collection is less costly because short distances between numerous waste producers allow for economies of scale and density (Hirsch, 1965; Stevens, 1978; Antonioli and Filippini, 2002; Koushki, Al-Duaij, and Al-Ghimlas, 2004). In addition, lower collection costs imply more and cheaper waste available for recovery. Moreover, policies tend to promote waste recovery rather than waste disposal in densely populated areas: high land prices reduce the competitiveness of landfilling and environmental nuisances associated with waste disposal and incineration tend to be less accepted because they affect a larger population. These considerations are confirmed by Berglund and Söderholm (2003), who find that population density has a positive and significant impact on waste recovery. In contrast, there is less reason to believe that density could serve as an instrument for the second endogenous variable, *mining*, as density can influence mining activities in opposite ways: for instance, density discourages economic activities generating local environmental nuisances, such as mining, but it reduces transportation costs, which raises the profitability of mining activities as ores are usually expensive to transport. This is confirmed by the results of the first stage regression, which show no significant impact of *Log* (*popdens*) on *mining* (see Table 20).

Turning next to the second instrument *education*, we consider that the percentage of high school graduates who successfully enroll in university is valid for both endogenous variables. The general point is that tertiary enrollment improves labor productivity (Moretti, 2004) and

[4]Employing the GMM-IV estimator in the case identified above is equivalent to performing a Two Stage Least Square IV estimator. In our base specification, equation (2.2) is just identified because we assume two endogenous regressors and use two instruments.

total factor productivity (De la Fuente, Ciccone, et al., 2003; Nicoletti and Scarpetta, 2003; Vandenbussche, Aghion, and Meghir, 2006). More skilled labor leads to more productive industries and more output in general, particularly in metal recovery and metal mining. The instrument also exhibits the second property necessary for validity, that is there is no theoretical reason why the level of education would directly influence raw material imports. We consider the additional instrumental variable, which is the country's level of knowledge in environmental technologies, as a variant of *education* which captures sector-specific knowledge. Like *education* it potentially improves productivity in the waste recovery sector.[5]

While GMM seems the most appropriate estimator to choose, we should acknowledge that it suffers from finite sample bias (Bond, 2002). When the panel data are balanced Kiviet (1995)'s correction of the Least Square Dummy Variable (LSDV) estimator is found to be more appropriate with small sample. However, balancing our sample leads to lose a significant number of observations and generating sample selection bias and reducing efficiency. Thus, we report only the GMM-IV estimates.

Non-stationarity is another potential concern. As pointed out by Saito (2004), GMM-IV can be highly biased when the data exhibit non-stationary series. We employ the group mean unit root test of Im, Pesaran, and Shin (2003) to test for stationarity of import,demand, recovery, and mining. Whether a serial correlation is assumed or not, the tests indicate stationarity for import,demand and recovery. Results for mining are ambiguous because in one version of the test, where we subtract cross-sectional averages from the series, the null hypothesis of non-stationary series cannot be rejected. In any case, as both the dependent variable and the variable of interest are stationary, our results should not be affected much by this issue.

Finally we compute standard errors that are robust to heteroskedasticity and autocorrelation because the homogeneity of serial correlation dynamics does not usually hold with aggregate data like ours.

[5]An alternative instrument for mining could be a country's metal ore endowment because this clearly impacts economic agents' decisions when it comes to extraction. Unfortunately, country-comparable data are not available.

2.3 Data

This paper examines imports of raw material between 1994 and 2008 in 21 developed and developing countries that vary by size of recovery sector. We now describe how we constructed the data set.

2.3.1 Measuring material imports and production

The dependent variable to measure import is the annual total import value of metallic raw material for 21 countries over the period 1994-2008.[6] These metallic raw materials include virgin raw materials (iron ore, copper ore, etc.) and secondary ones (ferrous scrap, copper waste and scrap, et cetera).[7] We cover ferrous metal, every base metal, gold and silver, and more than 10 other non-ferrous metals. Data comes from the United Nations (UN) Comtrade database. Our sample does not include some large importers like the United States and Canada for which some data necessary for the analysis are not available; we nevertheless cover 75% of total world trade.[8]

Ideally we would like perform the analysis for each different metal in order to control for material-specific factors. However, this is not feasible because the data describing domestic production (waste recovery, mining, and basic metal manufacturing) are only available at aggregate level. This also explains why the dependent variable is not expressed in quantity, but in value, as summing the quantity of different metals would be meaningless (such as adding tons of steel and gold).

Data on the annual production value of metal extraction, metal recovery, and basic metals manufacturing is taken from different sources. We obtain basic metals manufacturing output from the United Nations Industrial Development Organization (UNIDO) Industrial Statistics Database (INDSTAT2). Data on metal recovery annual output come from UNIDO

[6] The list of the countries is available in Table 14.

[7] See Table 15 and Table 16.

[8] Based on 2007 imports. The actual figure is slightly lower because our calculation is based on 72 countries for which data are available. The excluded economies are unlikely to weigh much in total trade.

INDSTAT4.[9] Data on the metal mining industry has proved much more difficult to collect. For the 21 countries included in our sample, a reliable source is the U.S. Geological Survey Mineral Commodity Summaries, which give the annual quantity of metals produced.[10] The problem is that we need the output of the mining sector in value. To estimate this output value, we thus multiply for each metal the annual quantity with an estimate of its world price, which is the average unit value of metal ore imports using trade data from the UN Comtrade database. To check the consistency of our measure, we calculate yearly correlations between this estimate and reported values in the OECD STructural ANalysis Database (STAN) database in the 9 countries for which the data is available.[11] The yearly correlations are around 0.98 from 1996 to 2006.

Aggregating different metals into single metrics by summing metal-specific values may generate measurement errors because the relative prices of the different metals can vary significantly over time. Changes in the value of imports or outputs can thus simply be driven by changes in relative market prices while quantities remain stable. To circumvent the problem, we deflate the values. As indices are not readily available for the set of countries and years included in the sample, we calculate our own price indices. For imports, we use a Tornqvist price index (see the formula in Table 17). The advantage of this type of index is flexibility, which is needed here because the degree of substitutability across products varies considerably: different metals are generally not substitutes (e.g., iron is not a substitute for copper) contrary to a virgin material and its secondary variant (e.g., virgin iron ore and ferrous scrap). The Tornqvist price index does not impose any restriction on the size of the elasticities of substitution between the goods. For waste recovery and metal mining, we rely on an arithmetic Paasche index as elasticities of substitution are very low, arguably zero (see Table 17 for details).[12]

[9] In the International Standard Industrial Classification of All Economic Activities (ISIC) 3.1, basic metals manufacturing is classified under Division 27 while metal recovery is classified under Class 3710.

[10] We collect the quantity in terms of metal content of Aluminum, Antimony, Chrome, Cobalt, Copper, Gold, Iron, Lead, Molybdenum, Nickel, Silver, Tin, Titanium, Tungsten, and Zinc because metal content per gram of ores differs from a mine to another.

[11] The mining industry is identified under division 13 in ISIC Rev. 3.1.

[12] We use the Paasche rather than the Laspeyres formula because the latter is not appropriate to deflate output at current prices IMF (2004).

All indices have a unique reference year. The main justification is that they are then less sensitive to price volatility than chained-base indices (Gaulier, Martin, Méjean, and Zignago, 2008). We proxy prices with the unit values of trade flows as we do when computing the output values of the mining sector. Kravis and Lipsey (1974) and Silver (2007) have highlighted the empirical problems implied by using this solution. We mitigate them by applying Gaulier, Martin, Méjean, and Zignago (2008)'s outlier management methodology to get "clean of outliers" price datasets. Their method consists in identifying two types of outlier, i.e. trade flow observations that are likely to have been rounded and observations that have unrealistic price variations over time for each importing country and product bundle.[13] These observations are not used when calculating average unit value since they could yield an unrealistic unit value.[14]

2.3.2 Other data sources

Data on population density and GDP per capita come from the World Bank and gross enrollment ratio in tertiary education comes from the UNESCO Institute for Statistics.

The variable $tariff$ is the simple average of effectively applied tariffs to proxy the trade protection of each country towards the import of metal raw materials. More specifically, we divide the sum of the simple average of effectively applied tariffs towards all countries of the HS6 products defined above by the number of HS6 products for which tariff data are available.[15] Data on tariffs at the HS 6-digit level are extracted from the United Nations Conference on Trade and Development (UNCTAD) Trade Analysis and Information System (TRAINS) database.

This indicator is specific to metallic raw materials and thus superior to more general measures, such as WTO membership dummies. However, it does not measure non-tariff barriers

[13] For instance a trade flow of 750 USD is reported as 1,000 USD.

[14] Recovery rates that are the share of total import value used to calculate the prices are available upon request.

[15] These are ad valorem tariffs. We do not use trade-weighted average tariffs for different reasons. First, they lack theoretical foundation (Anderson and Neary, 1996). More practically, they underestimate the level of trade barriers. In particular, prohibitive tariffs that totally block trade are not included because their weight is zero UNCTAD and WTO (2012).

to trade, such as countervailing duties and certain product regulations. Unfortunately, no sufficiently disaggregated data are available to construct a variable control for such barriers. We can however argue that non-tariff barriers are likely to be positively correlated with tariff.

The country's level of knowledge in environmental technologies, which we use as an additional instrument, is defined as the ratio between the stock of environmental patents and the stock of all patents.[16] This is a standard indicator in literature on green innovation (Dechezleprêtre and Glachant, 2014). We select granted patents classified as "General Environment" defined in the classification adopted in the OECD Patent Database and summarized in Table 19. We restrict our measurement to triadic or high-value patents to avoid flooding it with the numerous low-value patents. To account for technology obsolescence, we discount all stock by an annual depreciation rate of 15%, a value used in most literature. Data on patent filing come from the Worldwide Patent Statistical Database (PATSTAT) database.

2.3.3 Descriptive statistics

Table 2.1 gives the descriptive statistics. The final dataset is an unbalanced panel of 203 observations mainly limited by the availability of data on the metal recovery industry. Figure 2-1 shows the size of the recovery sector in 2007 for the countries included in the sample. Beside major western economies where ambitious recycling public policies have been implemented for several years (Japan, United Kingdom, Germany, France), note that China also has a well-developed waste recovery sector.

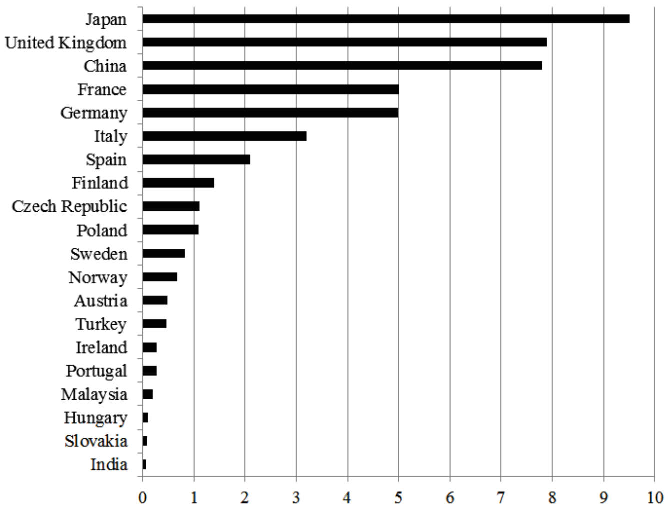
[16]The latter stock excludes Human Necessities and ICT patents because these two categories are very patent intensive and may overestimate the knowledge of industries located upstream in the value chain.

Table 2.1: Waste disposal cost difference and bilateral trade of unprocessed trade

Variables	N	Mean	Between Std. Dev.	Within Std. Dev.	Min	Max
Log (Import)	203	20.54	1.502	0.289	16.807	23.821
Log (Recovery)	203	19.624	1.646	0.598	16.505	23.929
Log (Mining)	203	18.107	2.486	0.493	11.46	24.02
Log (Demand)	203	23.103	1.575	0.183	19.497	26.606
Log (GDP per capita)	203	10.191	0.66	0.108	7.894	11.081
Tariff	203	0.613	3.238	0.69	0	19.51
Log (Population density)	203	4.539	0.936	0.026	2.662	6.213
Education (%)	203	53.428	19.409	8.136	9.78	97.51
Green Patent (%)	203	1.53	0.397	0.091	0.724	2.741

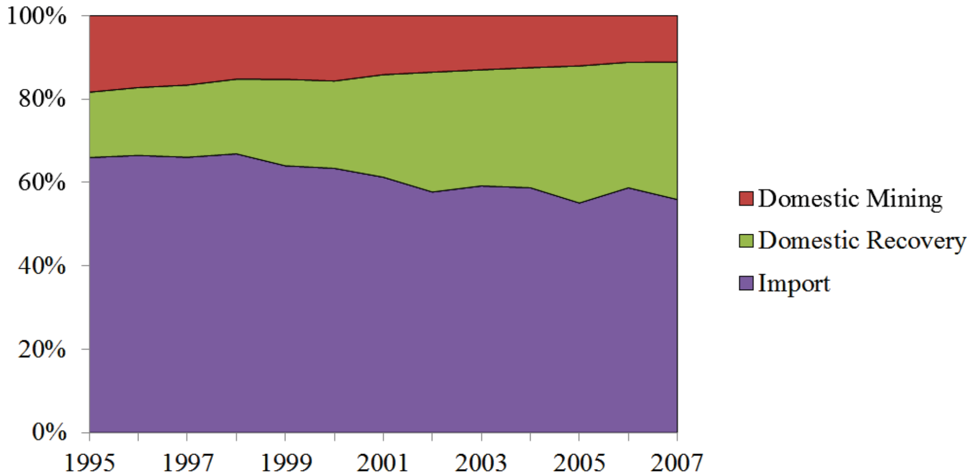
Notes. Import, recovery, mining, and demand are expressed in Billions 1994 USD. GDP per capita is expressed in purchasing power parity constant 2011 international dollars. Population density is expressed in people per square km of land area. Import, production and demand are expressed in constant 1994 USD. Nominal values are deflated using appropriate price indices (see section 2.1).

Figure 2-1: Metal recovery output in different countries.



Note. Output is expressed in billions current USD for year 2007. Data are not available for the Republic of Korea.

Figure 2-2: Relative shares of imports of metallic raw materials, domestic metal mining sector and domestic metallic waste recovery sector



Note. Average on 1995-2007 based on variables expressed in real USD for ten countries from the sample: Austria, Czech Republic, Finland, Hungary, Italy, Norway, Poland, Slovakia, Spain, Sweden.

Figure 2-2 plots the evolution of the shares of three material inputs used by the basic metal manufacturing industry: imported raw materials, secondary materials produced by the domestic waste recovery sector, and virgin materials produced by the domestic mining sector. Input levels are in real USD and are summed across a subset of 10 countries for which the data is available over the whole period.[17] The graph shows that imports constitute the main source of materials to meet demand in these countries. However, this share decreases over time, along with the value of locally produced virgin material. This is compensated by a boom in waste recovery, whose output more than doubles in 12 years. This could suggest that the development of recovery has induced a decrease in imports and domestic mining. The objective of the econometric analysis is to test the first hypothesis.

2.4 Results

Table 2.2 presents the main estimation results. Column 1 displays the estimates for the base specification (GMM-IV). In Column 2, we give the OLS fixed-effect estimates. This naive approach does not deal with the simultaneity issue and gives biased estimates. Column 3 and 4 are variants of the base specification that distinguishes the impact of recovery on virgin material imports (column 3) and secondary material imports (column 4). For every GMM-IV estimate, the Kleibergen-Paap rank LM statistic for under-identification is reported. The joint null hypothesis of the Kleibergen-Paap rank LM statistic is that equation (2) is under-identified in all cases. This provides strong support for the instrument set. We also report in Table 20 the first stage regressions performed during the GMM-IV estimation, which confirms our expectations about the impact of instruments on the two endogenous variables.

Results of the base specification indicate that the development of the metal recovery industry reduces total imports of metallic raw materials. The size of the coefficient estimate as an elasticity is substantial. All things being equal, a 10% increase in the output of the metal recovery industry is roughly associated with a 3.3% decrease in total imports of metallic raw materials with a 95% confidence interval [-6%, -1%]. Note that the OLS FE

[17] Austria, Czech Republic, Finland, Hungary, Italy, Norway, Poland, Slovakia, Spain, and Sweden.

would lead us to underestimate that effect (see column 2).

This 3.3% effect is not economically insignificant when considering the size of the metal recovery industry relative to the size of imports, since gross imports are eight times as high as the metal recovery industry on average (see Table 18). The calculated marginal effect for a mean observation – a country × year in which the size of the waste recovery sector and the imports are set at the sample mean – is a 56 million USD decrease in imports for a 100 million USD increase in the size of the domestic waste recovery sector.[18]

The fact that the relation is not *one to one* can be explained by the previously mentioned fact that virgin raw materials and secondary raw materials are not perfect substitutes. Models 3 and 4 tend to confirm this claim, as the impact of domestic recovery is mostly derived from a decrease in imports of secondary raw materials, while the impact on imports of virgin raw materials is negative, but not statistically significant. Another possible explanation is that a significant share of the secondary raw metal produced domestically is exported towards foreign markets, and thus does not serve as a substitute for imported metallic raw materials. The other coefficients present the expected signs. The demand variable increases imports. The influence of the size of the domestic mining sector is not significant, which is consistent with results of Model 3. Note that the control variable tariff is never significant, which is not that surprising as tariffs tend to be low for these goods - the average tariff is 0.6% - with limited variations – the standard variation is around 3% (see the descriptive statistics in Table 2.1).

[18] The precise formula is marginal effect $= elasticity \times \frac{imports_{mean}}{recovery_{mean}}$.

Table 2.2: GMM-IV and OLS estimates of country import values of metallic raw materials

	GMM-IV	OLS FE	GMM-IV	
	All imports	All imports	Imports of virgin material	Imports of secondary material
	(1)	(2)	(3)	(4)
Log (Recovery)	-0.326***	-0.099*	-0.25	-1.074**
	(0.117)	(0.051)	(0.188)	(0.510)
Log (Mining)	0.006	-0.005	-0.265	0.980*
	(0.194)	(0.044)	(0.413)	(0.565)
Log (Demand)	0.545*	0.502***	0.94	-0.968
	(0.301)	(0.116)	(0.706)	(0.801)
Log (GDP per capita)	0.693*	0.525	1.496**	1.675
	(0.376)	(0.547)	(0.629)	(1.534)
Tariff	0.034	0.001	0.124	-0.002
	(0.033)	(0.022)	(0.132)	(0.061)
Year dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Instruments	Log (Population density) Education	Log (Population density) Education	Log (Population density) Education	Log (Population density) Education
Kleibergen-Paap rank LM statistic	6.84***		7.23***	5.85**
R^2	0.35	0.75	0.04	-0.75
Observations	203	203	203	203

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include a constant not reported for clarity.
The dependent variable is the log of metallic raw material imports in value for models 1 and 2. For model 3 and 4, it is the log of metallic virgin materials and metallic secondary materials, respectively.

We perform multiple checks to assess the robustness of our results (see Table 2.3). We first look at the potential impact of outliers. In column 5, we replicate our base estimation but we drop China, which is the largest importer, metal miner, and basic metal producer. The coefficients obtained are similar in size to that obtained with the full sample.

We also test whether our results are sensitive to the price index used to deflate nominal metal recovery output or nominal import value into real terms. In column 6, import value is deflated using an arithmetic Paasche index. In column 7, metal recovery output is deflated using a Tornqvist index. The estimates obtained are respectively -0.305 and -0.294, which are close to our base specification estimate equal to -0.326.

To provide additional support to the validity of our instrumental variable approach, we replicate our base estimation using the share of green patents as an additional instrument in Model 8. Since we have more instruments than endogenous variables, we can then rely on the Hansen J-statistic. The over-identification test result indicates that we cannot reject the joint null hypothesis of the Hansen J-statistic that the instruments are valid. As we obtain a coefficient similar to that obtained in our base specification, this suggests that our overall identification strategy is valid.

Finally, we perform a placebo test in column 9: we replace the total import value of metallic raw materials with the total import value of agricultural commodities. Results are consistent because the coefficients of $Log\ (recovery)$, $Log\ (mining)$ and $Log\ (demand)$ are no longer significant.

Table 2.3: Robustness checks estimation results

	China dropped (5)	Alternative Price Index for Import (6)	Alternative Price Index for Recovery (7)	Additional Instrument (8)	Agricultural commodities (9)
Log (Recovery)	-0.333***	-0.305***	-0.294***	-0.400***	0.004
	(0.121)	(0.111)	(-0.1)	(0.148)	(0.057)
Log (Mining)	-0.009	-0.084	-0.052	0.113	0.171
	(0.196)	(0.203)	(0.193)	(0.184)	(0.105)
Log (Demand)	0.575*	0.428	0.663**	0.396	-0.129
	(0.312)	(0.309)	(0.311)	(0.284)	(0.163)
Log (GDP per capita)	0.794	1.091***	1.031**	1.059**	1.036***
	(0.484)	(0.412)	(0.408)	(-0.44)	(0.326)
Tariff	0.036	0.033	0.033	0.191*	-0.002
	(0.035)	(0.031)	(0.034)	(0.097)	(0.003)
Year dummies	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Instruments	Log (Population density) Education	Log (Population density) Education	Log (Population density) Education	Log (Population density) Education green patents	Log (Population density) Education
Kleibergen-Paap rank LM statistic	7.10***	6.84***	8.03***	6.86***	6.85***
R^2	0.33	0.37	0.39	0.26	0.65
Observations	197	203	203	199	203

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include a constant not reported for clarity.
All columns are estimated with the GMM-IV estimator.

2.5 Concluding remarks

Our results indicate that the metal recovery industry has a significant economic impact on imports of metallic raw materials: a 10% increase in the size of the domestic metallic waste recovery sector reduces imports by 3.3%; or equivalently, a 100 million USD increase in waste recovery leads to a 56 million USD decrease in imports. Further estimations suggest that the reduction concerns imports of secondary raw materials rather than imports of virgin materials. We thus confirm that recycling reduces dependence on an international supply of raw materials, a virtuous effect for countries with low resource endowment.

Given that recycling is generally more expensive than waste disposal, is it thus worth the extra cost?[19] This question goes well beyond the scope of this paper. Note however that existing cost-benefit analyses of recycling policies Kinnaman, Shinkuma, and Yamamoto (2014) do not take into account the potentially beneficial impact of recycling on resource dependence. Another aspect that we do not consider is the impact of domestic recovery on exports of secondary or virgin raw metallic materials. Hence, we are not able to look at the full impact of domestic recycling on the balance of trade. Another limitation is our focus on metallic waste, whereas other materials like paper, plastics and textiles are also recycled and traded internationally. Trade in metallic materials is however considerably greater (around 80% of global trade in secondary materials during the period 2009-2013).[20]

[19]EPA (1994) reported on the recycling operating and maintenance cost and landfill tipping fees for 23 U.S. communities from various U.S. states. In 1990, the average recycling operating and maintenance cost was 101.5 USD per ton and the average tipping fee was 49.5 USD per ton. Recycling operating and maintenance costs were higher than landfill tipping fees in 74% of communities.

[20]Based on author calculations from the UN Comtrade Database and products selected in Table 15 and Table 16.

International outsourcing and innovation in clean technologies[21]

Antoine Dechezleprêtre[2], Damien Dussaux[3], David Hemous[4], and Mirabelle Mûuls[5]

[2] *Grantham Research Institute on Climate Change and the Environment, LSE*

[3] *MINES ParisTech, PSL - Research University, CERNA - Center for industrial economics*

[4] *INSEAD*

[5] *Grantham Institute and Business School, Imperial College London*

Abstract

We examine the impact of low-cost imports of material products on firms' propensity to engage in input-saving ('clean') innovation using a dataset that combines firm-level international trade data with self-reported innovation data for around 6,000 French companies observed from 1994 to 2010. We find robust evidence that a higher share of 'material' imports from China and India significantly decreases firms' propensity to engage in 'clean' technologies. In other words, firms substitute clean innovation with material imports. A one standard deviation increase in the import share of 'material' products from these countries decreases firms' propensity to engage in environmental innovation by up to 15 percentage points. This suggests that trade with low-cost countries might have significantly reduced environmental innovation during the past 20 years.

Keywords: Imports, Environmental innovation, firm-product analysis

JEL Classification: F18, Q56, D22, L11, C25

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Chapter 3

International outsourcing and innovation in clean technologies

3.1 Introduction

From 1996 to 2011, the share of non-OECD countries' imports in OECD's total imports increased by 11 percentage points to reach 33%.[1] This important shift in the pattern of trade is a result of rising trade openness between developed and developing countries following the different GATT trade rounds. Trade in energy intensive goods, accounting for 50% of trade in all goods from non-OECD to OECD, is a major determinant of this general trend.

In this paper, we examine for the first time whether access to materials from low-cost countries reduces firms' incentives to develop clean technologies. This is an important question given the pressing challenges posed by climate change and other environmental issues. There are now empirical evidence that cross-country differences in environmental regulatory stringency led pollution intensive industries to relocate from stringent to lax countries (Ederington, Levinson, and Minier, 2005; Levinson and Taylor, 2008; Kellenberg, 2009; Kheder and Zugravu, 2012). This phenomenon, called pollution haven effect in the literature, reflects the failure of unilateral environmental policies to reduce worldwide levels of pollution in a

[1] Authors calculation based on Cepii's BACI database.

globalized world.

Here, we focus more specifically on how trade itself could influence green innovation dynamics. This is important for example in the case of climate change. As green technologies contribute to abate future emissions of greenhouse gases, their timing is key: it determines the cumulative levels of greenhouse gas in the atmosphere and hence the risk of dangerous climate change.[2] Providing incentives to develop new clean technologies has become a focus of environmental policy. It is not surprising, then, that understanding the determinants of clean technological change is a lively research area, both on the theoretical (Acemoglu, Aghion, Bursztyn, and Hemous, 2012) and on the empirical side (Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012; Veugelers, 2012). There are now several empirical evidence that environmental regulations lead to cleaner innovation.[3] As well as free trade shapes production output worldwide, it may also play an important role in determining innovation output and direction.

They are different ways how trade openness could impact firms incentive to innovate. First, higher trade openness could stimulate innovation because domestic firms face potentially higher competition from foreign firms. Several studies provide empirical evidence that firms operating in an industry where the degree of competition is high tend to be more innovative (Blundell, Griffith, and Van Reenen, 1995; Geroski, 1995; Nickell, 1996; Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Aghion, Bechtold, Cassar, and Herz, 2014). Second, trade openness in the presence of asymmetric environmental regulations could relocate not only production but also innovation.

In countries with strict environmental policies, firms have more incentive to reduce their emissions of pollutants. Companies have two strategies to comply with the regulations. First, they can innovate in clean technologies. Second, they can offshore a pollution intensive part of their production to countries with lower production costs. This second option becomes

[2]Timing is especially important as technologies may be path dependent that is it is easier to innovate in clean technologies if these technologies are already well developed. The cost to switch from dirty to clean technologies increases as the path of dirty technologies expends.

[3]Ghisetti and Pontoni (2015)'s meta-analysis shows that 78% of the models from the primary studies find that the environmental policy variable has a statistically significant effect on environmental innovation.

more profitable as trade costs get lower. Offshoring firms may have less incentive to innovate in general and especially in clean technologies. Nevertheless, offshoring may also change innovation behaviours in the sourcing countries.

The effectiveness of unilateral strict environmental innovation on net global green innovation may be undermined by international trade as it is the case for net CO2 emissions in a situation of carbon leakage. We can formulate several outcome resulting from the offshoring to low-cost countries under asymmetric environmental regulations. First, clean innovation is not induced anywhere and dirty innovations continue to prevail in both strict and lax countries. Second, clean innovation is induced in sourcing countries and not in the offshoring countries. We can coin this situation as a clean innovation leakage. Third, clean innovation is induced only in the offshoring countries and not in the sourcing countries. Finally, clean innovation is induced in both sourcing and offshoring countries. Which of these distinct outcome prevails is an empirical question.

In this paper, we provide the first part of the answer to this global issue by focusing only on the impact of offshoring to low-production cost countries on the propensity to innovate in clean technologies of firms located in countries having strict environmental regulations.[4] To investigate this question, we use theory to model jointly firms' trade and innovation behaviour. Our theoretical model predicts that trade with low-cost countries leads firms to undertake less material or energy saving innovations. This is because firms can reduce their variable cost of production by importing cheap intermediate goods from low-cost countries. By doing so, they have less incentive to innovate in order to increase materials productivity and lower their production cost.[5]

To test this prediction and quantify this effect, we combine self-reported innovation data from the Community Innovation Survey with detailed firm- and product-level trade data for a sample of nearly 6,000 French companies observed from 1994 to 2010. Firm-level data

[4]It is equally important to investigate the effect of offshoring on sourcing countries to measure the impact of asymmetric on net global clean innovation and long-run emission. However, it is not the focus of the present paper.

[5]Because they both require firms to pay a fixed cost, import and innovation can become, at some point, mutually exclusive strategies to reduce variable cost of production.

allows us to control for (observed) firm heterogeneity, in particular whether the firm is also an exporter, is big, and has high productivity. We use industry fixed effects to take unobserved differences between industries into account.

We use product classification information to identify imported goods that enter into the production of energy-intensive products. These 'material' goods include for example metal products, pulp, and refined petroleum. Information on the country of origin of imports allows us to estimate the relative cost of inputs faced by companies. We complement this firm-level trade data with data on 'clean' innovation activities carried out specifically to reduce the use of these inputs.

We find strong evidence that a higher proportion of 'material' imports sourced from low-cost countries has a negative impact on firms' propensity to engage in 'clean' innovation. This finding is stable across various definitions of what can be considered a low-cost country and to the way we define 'material' imports. The magnitude of the effect is large: at the sample mean, an increase in the import share of 'material' products from India and China in a firm's total 'material' imports by one standard deviation (a move from 3% to 16%) is predicted to decrease firms' propensity to engage in environmental innovation by 15 percentage points. To put this figure into perspective, one can observe that the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010. Thus, our results suggest that, ceteris paribus, trade with low-cost countries might have significantly reduced environmental innovation during the past 20 years.[6]

Our focus on the two largest fast-growing developing economies, China and India, is motivated by three reasons. First, as illustrated above, these countries have played a growing role in providing companies in developed regions with cheaper intermediate goods in the last two decades, particularly in labour-intensive sectors. Second, the competition from these emerging economies has given rise to heated policy debates over the pertinence of introducing measures to protect domestic industries. A third, more data-driven reason is

[6]Evidence suggests that, on the other side, competition from Chinese imports may have stimulated technical change in Europe Bloom, Draca, and Reenen (2011). Therefore trade might affect both the rate and the direction of technological change.

that the analysis showed that our results are unambiguously driven by China and India, although they are fully robust to considering other country groups such as BRICS countries (Brazil, Russia, South Africa, India and China) or low-wage countries.

This paper has important policy implications for the current debate on carbon 'leakage'. In a free-trade world, increased carbon prices following adoption of unilateral climate policies may generate a pollution-haven effect in other countries or regions, whereby foreign countries specialise in the production of carbon-intensive products in which they have a newly acquired competitive advantage and which they can subsequently export back to 'virtuous' countries. Environmental policies may thus fail to achieve their desired objective while destroying jobs in environmentally-friendly countries.[7] Our paper suggests that leakage may not only affect jobs and emissions in the short run. It also affects long-run emissions and competitiveness by reducing incentives for firms to conduct innovation in 'clean' technologies. This may provide further justification for policies to prevent leakage, such as border-tax adjustment.

Our paper relates to two strands of the literature. First, we build on the empirical literature on trade and technological change.[8] Previous studies have demonstrated that import competition, in particular from low-cost countries, has an influence on product innovation (Bernard, Jensen, and Schott (2006a); Iacovone, Rauch, and Winters (2010); Lelarge and Nefussi (2013)). Bloom, Draca, and Reenen (2011) show that Chinese import competition has led to increases in R&D expenditures, patents and total factor productivity among European companies. Goldberg, Khandelwal, Pavcnik, and Topalova (2010) and Colantone and Crinó (2011) have shown that cheaper imported inputs boost firms' performance and lead to the introduction of new products. However, none of these papers consider the empirical effect of firms' *own* imports on their innovative activity. To the best of our knowledge, the only paper that uses this approach is Bøler, Moxnes, and Ulltveit-Moe (2012), which examines the interdependence of R&D and intermediate inputs and their joint impact on firm's produc-

[7]Recent empirical papers show evidence of leakage, although this effect seems small (Levinson and Taylor (2008)). For example, Aldy and Pizer (2011) show that an increase in energy prices in the US following the introduction of a 15$/ton carbon tax would induce a domestic production decline of between 3 and 4 percent among energy-intensive sectors and a roughly 1 percent increase in imports.

[8]The theoretical literature on trade and technology is well developed and has been growing constantly since the seminal paper by Grossman and Helpman (1991).

tivity. Bøler, Moxnes, and Ulltveit-Moe (2012) find that importing increases productivity, which frees up resources that can then be used to increase innovation activity. Thus, trade affects the rate of technological change. In this paper, we show that importing may also affect the *direction* of technological change by reducing incentives for environmentally-friendly innovation.

Second, our paper relates to the vast literature on the determinants of environmental innovation. Many studies have used patent data to measure clean innovation (Popp, 2002; Brunnermeier and Cohen, 2003; Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012), but an equally large number of papers have instead used data from the Community Innovation Survey (Horbach, 2008; Frondel, Horbach, and Rennings, 2008; Rennings and Rammer, 2011; Rennings and Rexhäuser, 2010; Rexhäuser and Rammer, 2011; Horbach and Rennings, 2012; Leeuwen and Mohnen, 2013; Veugelers, 2012). Most of the recent literature has focused on the impact of environmental policy on innovation (see e.g. Newell, Jaffe, and Stavins (1999), Popp (2002), Brunnermeier and Cohen (2003) and Johnstone, Haščič, and Popp (2010)).[9] No study has yet looked at trade with low-cost countries as a determinant of 'clean' innovation.

The paper proceeds as follows. Section 3.2 develops the theoretical model used to analyse jointly firms' trade and green innovation behaviour. The empirical strategy is developed in Section 3.3. Section 3.4 describes our data set. We present the empirical results in Section 3.5. Some extensions and robustness tests are contained in Section 3.6. Section 3.7 concludes.

3.2 Model

In this section we present a very simple model to guide our intuition for the empirical investigation. We consider a two country economy where the two countries are Europe and China. Both countries are endowed with a given fixed mass of low-skill workers and Europe

[9]See Ghisetti and Pontoni (2015)'s meta-analysis for a comprehensive list of publications on the determinants of environmental innovation

is endowed with a mass of high-skill workers. Europe admits a representative agent whose utility is given by

$$U^E = C_0^E + \frac{1}{\alpha}\left(\int_0^1 C_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}\alpha},$$

where C_0^E denotes the European consumption of a homogeneous good, and C_i the consumption of a differentiated good. China admits a representative agent with utility $U^C = C_0^C$, with C_0^C the Chinese consumption of the homogeneous good. The homogeneous good is chosen as the numeraire and traded internationally. It is produced in both countries with low-skill labour with productivity w in Europe and w^* in China ($w > w^*$), such that low-skill wages are w in Europe and w^* in China. The differentiated good is produced monopolistically in Europe according to the production function:

$$Y_i = A_i\left((B_i Q_i)^{\frac{\varepsilon-1}{\varepsilon}} + H_i^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}},$$

where A_i denotes the overall productivity of variety i's production, B_i is the materials productivity for variety i, Q_i denotes the quantity of "aggregate materials" used for the production of variety i and H_i denotes the mass of high-skill workers hired for the production of variety i. H_i may represent the quantity of headquarters services or more complex intermediate inputs that go in the production of variety i. The quantity of aggregate materials is given by a Cobb-Douglas aggregate of a the amount of materials $j \in (0, 1)$:

$$\ln Q_i = \int_0^1 \ln q_{ji} dj,$$

where q_{ji} denotes the quantity of material j used in the production of variety i. Note that with the Cobb-Douglas structure, there is no loss of generality in assuming a general materials productivity B_i for variety i, a formulation with material-specific productivities b_{ij} would be equivalent. Materials are produced competitively with low-skill labour in Europe or in China at price w and w^* respectively.[10] However, importing material j from China involves a large investment and we assume that during the period under consideration, the producer

[10]Note that the lower cost of materials in China could also result from laxer environmental regulations.

of variety i can only import a share N_i^C of materials from China (Vogel and Wagner, 2010; Kasahara and Lapham, 2008; Andersson, Lööf, and Johansson, 2008; Castellani, Serti, and Tomasi, 2010).

Moreover at the beginning of a period, the producer of variety i inherits a productivity vector (A_i^0, B_i^0). She can invest in R&D to increase the productivity of technology A by a factor $\left(1+\gamma_i^A\right)$ at a cost $\psi\left(\gamma_i^A\right)$ (in units of the homogeneous good), and similarly she can increase the productivity of technology B by a factor $\left(1+\gamma_i^B\right)$ at cost $\psi\left(\gamma_i^B\right)$. We assume that the cost function ψ is increasing and convex with $\psi(0) = \psi'(0) = 0$. The empirical analysis interprets productivity improvements as discrete, while here, for simplicity, we represent them as incremental. This is, however, without consequence: we can consider that if γ_i^A is larger, the firm is more likely to report an innovation of type A (and similarly for γ_i^B).

3.2.1 Resolution of the model

The producer of variety i faces an iso-elastic demand $C_i = P_i^{-\sigma}\overline{P}^{\sigma+\frac{1}{\alpha-1}}$ where P_i is the price of variety i and $\overline{P} \equiv \left(\int P_i^{1-\sigma}di\right)^{\frac{1}{1-\sigma}}$ is the price index for differentiated goods. Maximization of profits imply that $P_i = \frac{\sigma}{\sigma-1}c_i$, where c_i is the cost of producing variety i. The cost of producing variety i is given by:

$$c_i = \frac{1}{A_i}\left(v^{1-\varepsilon} + \left(\frac{c_i^Q}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}},$$

where c_i^Q is the cost of sourcing one unit of aggregate materials and v is the wage of high-skill workers. Note that the relative demand for high-skill workers over aggregate materials is given by

$$\frac{H_i}{Q_i} = (B_i)^{1-\varepsilon}\left(\frac{c_i^Q}{v}\right)^{\varepsilon},$$

which is increasing in B_i if $\varepsilon < 1$. Therefore, we focus on the case where $\varepsilon < 1$, so that an improvement in B_i can be interpreted as a materials-saving innovation, while an increase in

A_i will be a general process innovation (or a product innovation, which can be interpreted as a new variety of higher quality).

Since materials are cheaper in China than in Europe, the producer of variety i imports a share N_i^C of its materials from China (and $N_i^E = 1 - N_i^C$ from Europe). We then get $c_i^Q = w^{1-N_i^C} (w^*)^{N_i^C}$. Therefore the cost of producing variety i is decreasing in the productivity levels A_i and B_i and it is decreasing in the share of materials that can be sourced from China N_i^C. Moreover, the ratio of expenditures on materials sourced from China over materials sourced from Europe is given by

$$\frac{w^* N_i^C q_i^C}{w N_i^E q_i^E} = \frac{N_i^C}{1 - N_i^C}, \tag{3.1}$$

where q_i^Z, $Z \in \{C, E\}$ indicates the quantity of materials j used in the production of variety i, when material j is sourced from country Z. Overall, we get that post-innovation profits are given by:

$$\Pi_i = \frac{\xi}{\sigma - 1} A_i^{\sigma-1} \left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C} (w^*)^{N_i^C}}{B_i} \right)^{1-\varepsilon} \right)^{\frac{1-\sigma}{1-\varepsilon}},$$

where $\xi = \overline{P}^{\sigma + \frac{1}{\alpha-1}} \frac{(\sigma-1)^\sigma}{\sigma^\sigma}$, profits are increasing in A_i, B_i and N_i^C.

The innovation decision results then from:

$$\max_{\gamma_i^A, \gamma_i^B} \frac{\xi A_{i0}^{\sigma-1} \left(1 + \gamma_i^A\right)^{\sigma-1}}{\sigma - 1} \left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C} (w^*)^{N_i^C}}{B_{i0} \left(1 + \gamma_i^B\right)} \right)^{1-\varepsilon} \right)^{\frac{1-\sigma}{1-\varepsilon}} - \psi\left(\gamma_i^A\right) - \psi\left(\gamma_i^B\right),$$

we assume that ψ is sufficiently convex that the problem is concave and admits a unique solution defined by the first order conditions with respect to γ_i^A and γ_i^B respectively:

$$\psi'\left(\gamma_i^A\right) = \frac{\xi A_i^{\sigma-1}}{\left(1 + \gamma_i^A\right)} \left(v^{1-\varepsilon} + \left(\frac{w^{1-N_i^C} (w^*)^{N_i^C}}{B_i} \right)^{1-\varepsilon} \right)^{\frac{1-\sigma}{1-\varepsilon}}, \tag{3.2}$$

$$\psi'\left(\gamma_i^B\right)=\frac{\xi A_i^{\sigma-1}}{\left(1+\gamma_i^B\right)}\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{(1-\varepsilon)}\left(v^{1-\varepsilon}+\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}-1}. \quad (3.3)$$

With ψ sufficiently convex, γ_i^A and γ_i^B are small, so that we can derive comparative statics ignoring that the right-hand side of the first order conditions depend on γ_i^A and γ_i^B. Following (3.2), the productivity increase in the level of general technology γ_i^A is increasing in the levels of productivities A_{i0}, B_{i0} and in the share of inputs sourced from China N_i^C. The intuition is the following: the lower the production costs already are, the bigger is the market share and therefore the more profitable an innovation is.

Similarly, γ_i^B is increasing in A_{i0}. Differentiating (3.3) with respect to N_i^C implies:

$$\psi''\left(\gamma_i^B\right)\frac{\partial\gamma_i^B}{\partial N_i^C}\approx\frac{\psi'\left(\gamma_i^B\right)\ln\left(\frac{w}{w^*}\right)}{\left(\left(\frac{vB_i}{c_i^Q}\right)^{1-\varepsilon}+1\right)}\left((\sigma-1)-(1-\varepsilon)\left(\frac{vB_i}{c_i^Q}\right)^{1-\varepsilon}\right). \quad (3.4)$$

The first term represents a scale effect which captures the same intuition as in the case of γ_i^A: if the share of materials sourced from China is greater, the market share is larger and productivity improvements are more beneficial. The relative importance of that effect increases is higher when the elasticity of substitution across varieties is larger, as then cheaper varieties get a larger share of the market. The second term represents a substitution effect, which is negative under our assumption that $\varepsilon<1$—so that high-skill workers are more complement to materials than materials are to each other. In this case, when materials become cheaper, they represent a lower fraction of production costs, so that innovating to reduce the cost of one effective unit of aggregate material becomes less interesting. That effect is relatively more important when ε is small, so that high-skill workers and materials are very complement, and when vB_{i0}/c_i^Q is large so that materials already represent a small share of production costs. Therefore a larger share of inputs sourced from China may lead to a decrease in innovation aiming at reducing the costs of materials, all the more that materials already represent a small fraction of costs. Note that the impact of a higher initial productivity for aggregate materials B_{i0} is similarly ambiguous.

Yet, taking the ratio of (3.3) with (3.2) gives:

$$\frac{\left(1+\gamma_i^B\right)\psi'\left(\gamma_i^B\right)}{\left(1+\gamma_i^A\right)\psi'\left(\gamma_i^A\right)} = \left(\left(\left(\frac{w^*}{w}\right)^{N_i^C}\frac{w}{vB_i}\right)^{\varepsilon-1}+1\right)^{-1}, \tag{3.5}$$

which shows that, unambiguously, innovation efforts are *redirected* from improving the productivity of materials to general innovation when the share of materials sourced from China increases.

3.2.2 Empirical prediction

The empirical investigation focuses on this last equation. In practice, however, we do not observe N_i^C but the share of imports coming from China and India, that is we observe $dirty\_share = \frac{w^* N_i^C q_i^C}{w\left(N_i^E - N_i^F\right)q_i^E}$, where N_i^F denotes the share of materials sourced from France. Using (3.1), we get:

$$\frac{N_i^C}{1-N_i^C} = \left(1-\frac{N_i^F}{N_i^E}\right) dirty\_share.$$

Under the assumption that firms which source a large share of their materials from China and India do not also source a large share of their inputs from France (at the expense of other developed economies), then $dirty\_share$ is a good proxy for N_i^C.[11] Furthermore, energy could be understood as one of the "materials" q_{ij}, so that innovations which reduce energy use per output can be embedded in increases in B_i. Alternatively if some of the materials q_{ij} are produced in-house, energy efficiency improvements amount to an improvement in this material productivity b_{ij}, and as explained above, the model with a single B_i index is equivalent to one with a continuum of b_{ij}. Therefore, equation (3.5) then delivers the following prediction:

Prediction *A firm with a larger share of dirty inputs sourced from China and*

[11] This is a very reasonable assumption. First Ireland is a small country, so most of its tradeable materials are likely to be imported, so that N_i^F should not vary much across firms. Second, if anything, firms which source inputs from China and India are more likely to be already more involved in international markets.

India undertakes more general process and products innovation. Controlling for the amount of general process and products innovation, it undertakes less materials- and energy-saving innovations.

It is important to underline that with only a cross-section we cannot make a causal inference between the share of dirty imports coming from China and India and the direction of innovation. To show this, assume that sourcing a share N_i^C of materials from China involves a fixed cost $f\left(N_i^C\right)$, with f increasing and convex. Then a firm will choose the share N_i^C of materials to be sourced from China as the solution to:

$$\max_{N_i^C} \frac{\xi A_i^{\sigma-1}}{\sigma-1}\left(v^{1-\varepsilon}+\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}}-f\left(N_i^C\right).$$

If f is sufficiently convex and satisfies Inada-type conditions, the problem will have a single interior solution, which satisfies:

$$f'\left(N_i^C\right)=\xi \ln\left(\frac{w}{w^*}\right) A_i^{\sigma-1}\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\left(v^{1-\varepsilon}+\left(\frac{w^{1-N_i^C}\left(w^*\right)^{N_i^C}}{B_i}\right)^{1-\varepsilon}\right)^{\frac{1-\sigma}{1-\varepsilon}-1}.$$

N_i^C is increasing in A_i: the larger is the level of general productivity the more materials are sourced from China, which is due to a scale effect. The impact of a higher aggregate material productivity on the share of materials sourced from China exactly mirrors the analysis of the reverse relation, there is a scale effect which pushes towards more outsourcing from China, and a substitution effect which pushes towards less, the scale effect dominates when (3.4) is positive.

3.3 Empirical Strategy

3.3.1 Ordered probit model

In this paper we empirically test the intuition about the direction of innovation developed above. In the theory section, we assumed that innovation was a continuous process for clarity of exposition. However, what we actually observe is a discrete intensity of environmental innovation.[12] In our data, firms report a score from 0 to 3 quantifying the importance of energy or material saving innovation in firm innovation strategy and is described in full detail in Section 3.4 or table 23 in Appendix 4.7. A score of 0 means that material or energy saving technologies are 'not relevant' in the firm innovation strategy. Conversely, a score of 3 means that these technologies are highly important for the firm innovation strategy. Accordingly, our empirical method uses an ordered-probit model to estimate firm's environmental innovation intensity at time t conditional on some covariates. More specifically, we estimate:

$$\overline{EnvInnov_{it}} = \alpha ImportShare_{it} + \beta X_{it} + \delta_j + \lambda_t + \epsilon_{it} \tag{3.6}$$

where $\overline{EnvInnov_{it}}$ is that latent continuous version of the observed dependent variable $EnvInnov$ which is the intensity of environmental innovation in firm i innovation strategy during the period t.

Our main variable of interest $ImportShare$ is the share of 'material' imports from China and India in total 'material' imports of the firm, which proxies for the average cost of inputs faced by companies.[13] We check in Section 3.6 that our results are robust to using various country groups, import shares and to the way we define 'material' products.[14] Note that we do not have information on total input consumption, but only on total imports by companies. This feature of the data is an advantage since importing firms might differ systematically

[12]It is easy, however, to replace the continuous innovation process in the theory section by a probabilistic process, or even simpler, to consider that firms actually improves productivity continuously and self-report that it belongs in the upper category only when the improvements are large enough.

[13]Why not use directly the average input prices paid by firms? First, there is an obvious data constraint: input prices are a private information and collecting it for all the companies in our sample would be impossible. Second, we can reasonably assume that average input prices are negatively correlated with the share of inputs sourced from low regulation countries, and we check this on energy prices. IEA data show that Non-OECD countries have consistently had electricity prices between two and three times cheaper than OECD countries since the end of the 1970s.

[14]See section 3.4.2 for the definition of 'material' products.

from non-importing firms. In particular, firms that do not import at all might have more financial capabilities available to pay for the fixed cost of innovation.

We include a number of firm level controls X that include firm size, labour productivity, firm assets, exporting status, and its number of sourcing countries. We also include a comprehensive set δ_j of 4-digit level industry dummies of the NACE classification and a comprehensive set λ_t of period dummies. Section 3.4 provides greater detail on the data and the variables used in the estimations.

3.3.2 Endogeneity issues

One of the main issues we face in our empirical investigation is the endogeneity of our variable of interest. We identify two sources of endogeneity. The first source is simultaneity. On the one hand, we expect that importing a larger share of 'material' inputs from low-cost countries might have a negative impact on the probability that a firm introduces an environmental innovation. On the other hand, input-reducing innovation might symmetrically reduce the incentive for firms to source inputs from these countries because offshoring is costly.

The second source of endogeneity is due to omitted variables. Potential omitted variables are the degree of competition and firm's credit constraint. If the degree of competition is high, firms have more incentive to look for the cheapest inputs and these are supplied by low-cost countries. In the presence of adoption cost, Holmes et al. (2008) show that producers in highly competitive industries have more incentive to develop new technologies. Firms that are under credit constraint cannot incur the fixed cost of importing as well as spend more in R&D to innovate. Omitting the degree of competition or credit constraint would result in an upward bias.

We address these endogeneity issues using an instrumental variable strategy. Our instrumental variable captures the competitiveness of low-cost countries in the European Union market for the input bundle of firm i. It is calculated as follows:

$$IV_{it} = \frac{\sum_{k \in \mathcal{K}} (M_{i.k.} ShareEU_{kt})}{\sum_{k \in \mathcal{K}} M_{i.k.}} \tag{3.7}$$

where

$$ShareEU_{kt} = \frac{\sum_{l \in \mathcal{L}} M_{EUklt}}{\sum_{l} M_{EUklt}} \tag{3.8}$$

is the ratio between 'material' imports of the EU member states (except France) from low-cost countries and total 'material' imports of the EU member states (except France) calculated for each product k. M_{iklt} is the import of firm i of product k from country l, $\mathcal{K}$ denotes the set of material goods, and $\mathcal{L}$ denotes the set of low-cost countries.

If low-cost countries sell goods at low price, they should represent a significant share of European imports. If these goods are attractive for the EU as a whole, it should be attractive for French firms as well. Therefore, our instrumental variable should be correlated with the variable of interest and should be strong. We do not see a clear link between the imports of the EU that excludes France and French firm propensity to engage in green innovation. Thus, we believe that our instrument is valid.

3.3.3 Sample selection issue

Sample selection is another empirical issue we have to address. As we explain in the next section, only firms that innovate at period t actually provide a score for environmental innovation. Therefore, innovative firms are selected. The solution we adopt is standard and consists in two steps. In the first step, we estimate a probit selection model where the dependent variable is a binary variable equals to 1 when the firm innovates:

$$Pr(Innov_{it} = 1) = \Phi(\alpha ImportShare_{it} + \beta X_{it} + \delta_j + \lambda_t + \gamma Spillover_{it} + \upsilon_{it}) \tag{3.9}$$

where Φ is the cumulative normal distribution. $Spillover_{it}$ is the selection variable that influences the probability that firms i innovate in general but shall not impact the importance of green innovation. The selection variable is calculated as the ratio between the number of firms in the same 4-digits NACE industry as i that are located in the same geographical area and that introduce at least one innovation in period t and the total number of firms in that same industry and in that same geographical area.[15] If other firms competing in the same market are innovative, it provides more incentives for any firms to innovate as well. In addition, innovations made by some firms may also spill over to some other firms. Thus, we expect γ to be positive. Conditional on the other regressors, we do not believe that $Spillover_{it}$ impacts the score of environmental innovation in equation 3.6 so that it is a valid exclusion restriction.

The second step of our identification strategy is to include the inverse Mills ratio as an additional control in our final structural equation:

$$\overline{EnvInnov_{it}} = \alpha ImportShare_{it} + \beta X_{it} + \delta_j + \lambda_t + \rho m_{it} + \epsilon_{it} \tag{3.10}$$

where m_{it} is the inverse Mills ratio obtained from the probit selection model 3.9. We expect ρ to be positive and significantly different from 0.

3.4 Data

Our data are a composite of three main data sets on French manufacturing firms. Data on environmental innovation come from 6 waves of the Community Innovation Survey. International trade data are provided by the French Customs authorities. Finally, firm-level information (such as turnover, capital, etc.) comes from the Ficus database of Insee. Below we describe each of the data sets in turn.

3.4.1 Environmental innovation data

We use the CIS data to construct our set of dependent variables. The CIS data set contains survey data and covers only a fraction of the population of French firms present in

[15] Here, the geographical area is the French department. The departments are administrative divisions of France and amount to a number of 101.

our other data sets described below. The CIS asks French firms about their activity in terms of product and process innovation, R&D, cooperative behaviour in research and innovation alliances over the last three years before the survey. The waves covering the years 1994 to 2008 include a set of questions on environmental innovation.[16] For each wave, the survey asks how important were innovations that reduce either the use of material or energy per unit of output in firm's decision to innovate during the last three years. Firms have four exclusive choices: 'not relevant', 'low importance', 'medium importance', and 'high importance'. We translate the answer into a discrete score from 0 to 3 as explained in the section above.[17] The survey questions related to environmental innovation are presented in the Appendix.

In our selection estimation sample, on the firms answering the CIS survey, around 60% introduced a new innovation. In our final estimation sample, this number is around 85% and further illustrates the need to address the sample selection issue. Looking at green innovation, 65% of the firms in the our final estimation sample considers material or energy saving technologies as relevant for their innovation strategy. Table 3.1 provides the share of each score category by period of time. As the composition of the sample change over time, it is not possible to comment about the evolution of these shares. However, we can make two remarks. First, the variable is almost uniformly distributed across each categories and this holds for every period. This means that the survey is somewhat successful at ranking firms and that we will have good variation in the variable of interest.[18] Second, most of the firms reports that material or energy saving technologies have a medium importance in their decision to innovate in most periods.

[16]Note that there was no survey for 1996-1998 and 2000-2002.

[17]The survey question about environmental innovations takes a different form for the 2006-2008 wave. Instead of being asked how important are green technologies in their innovation strategy, firm were asked whether they had introduced a material saving innovation and whether they had introduced an energy saving innovation. When firms introduced neither, we allocate them a score of 0. When firms introduced one of the two innovations, we allocate them a score of 1.5. Finally if the firms introduced both innovations, we give them a score of 3. When estimating our model without the 2006-2008 wave, we get very similar result.

[18]We would have been worried about the quality of the data if 90% of the firms were concentrated in only two score categories.

Table 3.1: Environmental innovation score

Period	1994-1996	1998-2000	2002-2004	2004-2006	2008-2010
Not relevant	22%	25%	20%	28%	22%
Low importance	25%	28%	26%	24%	25%
Medium importance	29%	28%	29%	26%	29%
High importance	24%	19%	25%	22%	24%
Nr of firms	1,112	1,320	1,977	1,707	1,513

3.4.2 International trade data

International trade data are collected by the French customs authorities. The data include firm-level information on imported products, including information on the country of origin. International trade data contain information on all French firms involved in exporting or importing activities and reporting their transactions to the customs authorities.This data set includes information on the country of origin of imported products and on the country of destination of exported products, value and quantity (in tonnes), product classification at CN8 level (8-digit level of Combined Nomenclature classification) and, where available, corresponding Prodcom code.The international trade data are available for a period of 1994-2010.

To construct our main variable of interest we use information on product codes, transaction value and origin country of imports. Our theoretical model provides predictions about 'material' goods. They are intermediate goods that are not 'complex'. For instance, they include primary plastic, crude steel, wood pulp, etc. [19] 'Material' goods exclude 'complex' intermediate goods such as computer motherboards or bodies for motor-vehicles that are used to produce final goods. We use the Global Industry Classification Standard (GICS) to classify CN8 goods into material goods or not. The GICS defines a 'material' sector that contains several manufacturing industries: chemicals, construction materials, glass, paper, forest products and related packaging products, metals (including producers of steel), minerals and mining.[20] The first two digits of the CN8 matches with the definition of the material

[19] We do not say that these products are not sophisticated.

[20] The Global Industry Classification Standard can be found here: https://www.msci.com/resources/pdfs/GICSSectorDefinitions.pdf

sector of the GICS. However, plastic products are absent from the GICS definition. As they are as material as steel or paper products, we decide to add plastics products found in the trade CN8 in the material category. Selected CN8 codes for material can be found in table 21 in the Appendix.

As we focus on environmental innovation, we also look at another category of goods: energy intensive goods. They consist in fuels and products from industries that are covered by the European Union Emission Trading Scheme (EU-ETS). We use Prodcom codes to map products into a 2-digit NACE classification. We use this mapping to identify products traded in the following energy-intensive industrial sectors: pulp and paper; coke, refined petroleum and nuclear fuel; non-metallic products; basic metals; fabricated metal products (except for machinery and equipment). These sectors are those covered by the EU ETS.

We then identify certain regions of the world with laxer environmental standards. We focus on China and India but show robustness of our results to considering BRIC countries and low-wage countries. We then combine import origin and product information to identify 'material' products from 'low-cost' origins to construct our main explanatory variable: a firm's share of 'material' imports from Southern countries in its total 'material' imports. This variable is defined as the value of 'material' products imported from China and India during the first two years of a CIS period divided by the value of total 'material' imports of a firm in these same two years.[21] Multiplying this by 100 we obtain a percentage share of 'material' imports from a specific 'material' region (China and India or BRIC).

We also use the trade data set to construct two control variables. The first is an exporter dummy which equals 1 if a firm is reporting exports in a given year and 0 otherwise. The second is the number of different countries that ship any good to the firm.

3.4.3 Financial data and estimation sample

The financial data on manufacturing firms come from two main data set. The first is the

[21] We take only the first two years of each period instead of three to avoid having overlapping observations. We show below that it does not affect our result.

Unified and Comprehensive File of SUSE (FICUS) database. FICUS is based on an annual fiscal census of manufacturing, mining and utilities firms called Unified Corporate Statistics System (SUSE). SUSE is conducted by the French Ministry for the Economy and Finance at the firm level.[22] SUSE covers all firms that are under the (industrial and commercial benefit) BIC tax system or under the (non commercial benefit) BNC tax system. Simply, SUSE covers all firms that send their tax return to the French Ministry for the Economy and Finance.

The FICUS data set on manufacturing firms provides an unbalanced panel covering over 3 millions firms for a maximum of 14 years for the 1994-2007 period. Three kinds of variables are available. First, there are firm information such as primary industry classification (at 2-4 digit NACE level), head office address, employment (measured as total employed), date of creation, etcetera. Second there are profit and loss account (income statement) variables such as total turnover, export, total labour costs, total gross earnings, etcetera.Finally, there are balance sheets variables such as the stock of capital, debt, etcetera.

The second data set for financial data is the Annual business survey (EAE) on the manufacturing industry.[23] In contrast with SUSE, it is not a census but a statistical source. Firms having at least 30 employees or a annual turnover of at least 5 millions euros must reply to the survey. However, the other manufacturing firms are randomly sampled. The EAE data set on manufacturing firms provides an unbalanced panel covering on average 21,000 firms accounting for 2,9 millions of workers. The EAE data set contains almost the same variables as FICUS. For the period 1994-2007, we merge EAE and FICUS and keep data of the latter when the data for a firm is available in both data sets because FICUS is a census and thus considered as more reliable. To obtain data for 2008, 2009, and 2010 we use the FARE file, the data set that replaced both EAE and FICUS from 2008.[24]

[22] For more information on the other data set described here, see the web-site of the French National Institute of Statistics and Economic Studies at http://www.insee.fr/en/methodes/default.asp?page=sources/ope-enq-suse.htm.

[23] For more information on this and other data sets described here, see the web-site of the French National Institute of Statistics and Economic Studies at http://www.insee.fr/en/methodes/default.asp?page=definitions/enquete-annuelle-entreprises.htm.

[24] FARE stands for Approached File of ESANE Results. ESANE stands for Annual Business Statistics Production. No web page in English exists at the time we write this paper.

We use the fiscal data set composed by FICUS, EAE, and FARE to control for observed firm-level characteristics. Firstly, we account for firms' productivity in two ways. We control for firm's labour productivity, measured as a total turnover per employee per firm-year. To the labour productivity measure we add a control for capital which is the book-value of capital net of depreciations. Secondly, since larger firms may have more resources available to engage in innovative activities, we include total employment in order to control for firm size. As for the variable of interest, we calculate for these control variables the first two years average for each period.

We match the three data sets together using the French firms national identification number contained by every data set. Most of the trading firms in the fiscal data set (see below) are found in the international trade data set. Our estimation sample is the intersection of the three data sets described above. This represents around 6,000 companies, depending on the model. As most companies surveyed by the CIS are also present in the trade data set, the limiting factor is the presence in the CIS data set. It is important to note that our final sample is unbalanced since more than 50% of the firms are observed only for one or two periods. The number of firms decreases as the number of available periods increases. Only 15% of the firms have more than four periods. Fewer observations are dropped because one of the two years needed to calculate the average for the control variables is missing. The share of the total number of firms by industry is given in Table 31 in Appendix 4.7. We note that beverages and tobacco are the only industries absent from the sample. On the 30 industries, nine industries industries represent less than 1% of the firms. The remaining 19 industries are well represented in the data. Table 23 in Appendix 4.7 presents a full list of variables used in this analysis and their definitions. Table 24 in Appendix 4.7 provides summary statistics of the main variables.

3.5 Importing and innovation

This Section presents the outcomes of our main estimations. As our econometric model is non-linear we then interpret our findings and discuss the magnitudes of the effects.

3.5.1 Main results

Table 3.2 presents our main results. We investigate the impact of firms' share of 'material' imports from China and India on the importance given to material or energy saving innovations by innovating firms (see equation 3.10). In column 1 the dependent variable is a score from 0 to 3 qualifying the importance of material or energy saving in firms' decision to innovate as explained in more details above. In column 2 the dependent variable is a dummy variable equal to 1 when the score is superior to 0. Column 1 is our base specification because we deal with endogeneity and selection issues and also model green innovation more accurately because of the ordinal nature of the dependent variable. The probit estimation of column 2 allows us checking the robustness of our results but also obtaining the marginal effects of import on the propensity to introduce a green innovation.[25]

We find that the share of 'material' products imported from China and India has a negative and significant effect on material or energy saving innovation as being important objectives in firm decision to innovate.This suggests that if a firm has been relying relatively more on imports from emerging economies, it has fewer incentives to engage in innovative activity that brings environmental benefits. It is likely that cheaper inputs make the prospect of paying out a fixed cost to engage in input-reducing innovation less attractive as the marginal benefits of reducing material or energy use would be smaller for import-reliant firms. This finding is robust across various models.[26] Our results show that there is therefore a direct trade-off between importing cheaper inputs and trying to reduce their use by way of introducing a new technology.

We find that the inverse mills ratio is always significant. This is not surprising given that the selection issue is obvious in our empirical investigation. It also means that it is important to deal with selection to identify equation 3.6 correctly. We find that the coefficient of the

[25]See Section 3.4 or table 23 in Appendix 4.7 for a detailed description of various dependent variables.

[26]Restricting the set of industry dummies at the 2 digits NACE level has no impact on the coefficients and on the outcome of the student test.

Table 3.2: Share of 'material' imports from China and India and propensity to carry out environmental innovation

Dependent variable	Importance given to material or energy saving innovation on a scale from 0 to 3	Equals 1 if the importance of material or energy saving innovation is not 0
	Ordered-IV-Probit (1)	IV-Probit (2)
Share of 'material' imports from China & India in all 'material' imports	-0.012** (0.005)	-0.011** (0.006)
Exporter (0/1)	0.282*** (0.056)	0.323*** (0.063)
Number of sourcing countries	0.001 (0.003)	0.002 (0.004)
ln(*Capital*)	0.029 (0.021)	0.061** (0.026)
ln(*Size*)	0.239*** (0.027)	0.234*** (0.033)
ln(Labor Productivity)	0.124*** (0.030)	0.051 (0.038)
Inverse Mills Ratio	0.647*** (0.030)	0.670*** (0.028)
Number of observations	10,355	10,155
Number of firms	5,873	5,785
First-stage IV coefficient	0.492***	0.501***
Industry-level dummies (NACE 4 digits)	Yes	Yes

Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
All columns include a comprehensive set of period dummies and a constant (not reported)

exporter dummy variable is always positive and statistically significant, suggesting that the exporting firms introduce more green innovation than non exporting firms. The number of countries from which firms import their input have no significant impact on firm propensity to carry out environmental innovation. The coefficients of size and labour productivity are always positive and significant, suggesting that bigger and more productive firms are more likely to introduce green innovation. As for other controls, more capital intensive firms are more likely to introduce environmental innovation in 2 out of 4 estimations. The signs of the coefficients of the control variables are not surprising.

In summary, our results offer strong support for our hypothesis. Firms that are more reliant on 'material' imports from emerging economies are significantly less likely to engage in environmental (energy- and material-saving) innovation. This suggests that importing cheaper inputs and carrying out 'clean' innovation are two substitutable strategies for companies.

3.5.2 Magnitudes

The non-linear nature of probit and ordered-probit models does not allow us to interpret the coefficients in table 3.2 straight away. Table 3.3 presents the results in terms of marginal effects.[27] Based on the IV-ordered-probit estimation, we find that the effect of import on innovation is large. In column (1), we find that a one percentage point increase in the share of 'material' inputs sourced from low-cost countries leads to an increase in the probability of material or energy saving technologies being *irrelevant* by 0.47 percentage points. In column (4), we find that a one percentage point increase in the share of 'material' inputs sourced from low-cost countries leads to a decrease in the probability of material or energy saving technologies being *highly important* by 0.36 percentage points. We find similar magnitude for the simple IV-probit estimation: a one percentage point increase in the share of 'material' inputs sourced from low-cost countries leads to a decrease in the probability of material or energy saving technologies being *relevant* by 0.42 percentage points.

In order to assign some economic significance to these magnitudes, we calculate the change in the predicted outcome probability in two scenarios - an increase in the import share of 'dirty' products from China and India by 1 standard deviation from the sample mean and a more prominent increase of this import share from 25% to 50%. Results are reported in table 3.4.

The mean value of the 'material' imports share is not very high in our data (around 3%). This is due to the large number of zeros in the data set. There is, however, a substantial heterogeneity amongst firms in their importing behaviour and the standard deviation is therefore quite high. A one standard deviation increase entails a change in the share of 'dirty' imports supplied from China and India from 3% to 16%. Such an increase is predicted to increase the probability that firms do consider material or energy saving technologies being

[27]To get convergent estimation of the marginal effects, we use a set of industry dummies at the 2 digits NACE level. It is not an issue since the estimation results of table 3.2 with 4 digits NACE are very similar to the results when considering the 2 digits NACE.

Table 3.3: Share of 'material' imports from China and India and propensity to carry out environmental innovation, marginal effects

Dependent variable	**Importance given to material or energy saving innovation on a scale from 0 to 3**				**Equals 1 if the importance of material or energy saving innovation is not 0**
	Score = 0	*Score* = 1	*Score* = 2	*Score* = 3	*Score* > 0
	Ordered-IV-Probit				IV-Probit
	(1)	(2)	(3)	(4)	(5)
Share of 'material' imports from China & India in all 'material' imports	0.0047***	0.0005***	-0.0015***	-0.0036***	-0.0042**
	(0.0016)	(0.0002)	(0.0005)	(0.0012)	(0.0017)
Exporter (0/1)	-0.0947***	-0.0108***	0.0296***	0.0739***	0.1223***
	(0.0184)	(0.0022)	(0.0058)	(0.0144)	(0.0205)
Number of sourcing countries	-0.0024**	-0.0003**	0.0008**	0.0019**	0.0027*
	(0.0011)	(0.0001)	(0.0003)	(0.0009)	(0.0014)
ln(*Capital*)	-0.0157**	-0.0018**	0.0049**	0.0123**	0.0240***
	(0.0069)	(0.0008)	(0.0021)	(0.0054)	(0.0083)
ln(*Size*)	-0.0709***	-0.0081***	0.0221***	0.0553***	0.0689***
	(0.0090)	(0.0012)	(0.0030)	(0.0070)	(0.0109)
ln(Labor Productivity)	-0.0351***	-0.0040***	0.0109***	0.0273***	0.0122
	(0.0098)	(0.0012)	(0.0031)	(0.0077)	(0.0125)
Inverse Mills Ratio	-0.2088***	-0.0238***	0.0652***	0.1628***	0.2152***
	(0.0100)	(0.0020)	(0.0040)	(0.0076)	(0.0095)
Number of observations	10,553	10,553	10,553	10,553	10,551
Number of firms	5,962	5,962	5,962	5,962	5,960
First-stage IV coefficient	0.5127***	0.5127***	0.5127***	0.5127***	0.5129***
Industry-level dummies (NACE 2 digits)	Yes	Yes	Yes	Yes	Yes
Firm fixed-effect	No	No	No	No	No

Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
All columns include a comprehensive set of period dummies and a constant (not reported)

irrelevant by 6 percentage points and decrease the probability that firms do consider these green technologies as *highly important* by 4 percentage points.

The same increase is predicted to decrease firms' propensity to engage in green by a range of 15 percentage points. To put this figure into perspective, consider that the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010. This suggests that, all else being equal, trade with China and India might have significantly reduced environmental innovation during the past two decades.

When we consider an increase in 'material' imports share from 25% to 50% the estimated decrease in the probability to engage in green innovation is around 30 percentage points, illustrating the non-linearity of the impact. The marginal impact of a higher reliance on Southern imports decreases as this reliance grows.

Table 3.4: Quantification of the results

	Ordered-IV-Probit Shift in the probability of a green innovation score being equal to 0	 1	 2	 3	IV-Probit Shift in the probability of a green innovation score superior to 0
1 standard deviation increase in imports of 'material' products from China and India reduces propensity to innovate by	**+6pp**	**+0pp**	**-2pp**	**-4pp**	**-15pp**
25% to 50% increase in imports of 'material' products from China and India reduces propensity to innovate by	**+12pp**	**-2pp**	**-5pp**	**-6pp**	**-30pp**

Derived after probit estimations in tables above. Response given in percentage point changes (pp).

3.6 Robustness Checks

We have performed a number of robustness checks to corroborate the main results reported in Section 3.5 and we describe them in this section.[28] As we have identified environmental innovation reducing either material or energy use per output as the closest substitute to increasing the share of 'material' imports form China and India, we report most robustness checks using this definition of environmental innovation.

3.6.1 Endogeneity and unobserved heterogeneity

Omitted variable bias and simultaneity bias

In section 3.3, we explained that a standard Ordered-Probit estimate suffers from two sources of bias. The first bias results from the simultaneity between the decision to import and the decision to innovate. If engaging in environmental innovation causes firms to lower their import from low-cost countries, then there is reverse causality and the naive estimator is biased downward. The second bias comes from omitted variables such as the degree of competition in the firm's industry and firm's credit constraint. For each omitted variable, its correlation with the dependent variable has the same sign as the correlation with the variable of interest.[29] This generates an upward bias in the naive estimate.

[28]Not all output tables are shown here for reasons of parsimony but all are available on request.
[29]The correlations are both positive for the degree of competition and both negative for firm's credit

In table 3.5 column 1 contains the estimated coefficient for the naive Ordered-Probit estimator and column 3 contains the estimated coefficient for the naive Probit estimator. In column 2 and 4, we report our main results presented in table 3.2 for comparison. The point estimate is highest (in absolute terms) when we instrument the variable of interest. If we assume that our instrumental variable is valid, this result supports the idea that the upward bias is larger than the downward bias in the naive estimation. We are currently working on an alternative instrumental variable to check the robustness of our result.

Unobserved heterogeneity

Controlling for unobserved heterogeneity is difficult in discrete panel data models like the one we employ. This is because one cannot difference out the unobserved term using first difference or the within transformation since these models are not linear. Point identification can be achieved for binary panel data model but requires strong assumptions and is not robust to misspecification. For instance, Chamberlain (2010), Honoré (2002), and Honoré and Kyriazidou (2000) show that point identification in parametric discrete panel data model fails unless the time dependent unobservables are independently and identically distributed with a logistic distribution. Manski (1987) shows that point identification is achieved if at least one regressor have unbounded support. Because these identifying assumptions are so strong, recent econometric research focus on partial identification that requires much weaker assumptions. [30]

Here, we try to control for as much observed heterogeneity as we can using many firm-level control variables. Some of these control variables can be themselves caused by the variable of interest. Offshoring causes the re-allocation of labour and the sell of capital of the unit of production. It may also affect labour productivity since unit of productions' labour productivity is likely to differ along the production value chain. As the share of 'material' imports from low-cost countries in firm's total imports can be seen as a proxy for offshoring, our control variables can be outcome of the variable of interest. Angrist and

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constraint.

[30]See for instance Chesher (2010), Chesher and Smolinski (2012), Chesher (2013), Chesher and Rosen (2013), and Chesher, Smolinski, and Rosen (2013).

Pischke (2009) argue that such control variables are 'bad' because they can bias the estimate of the coefficient of interest.

In table 3.6, we run regressions where we drop different subset of control variables. We report our base specification in column (1) to allow for comparison. The coefficients obtained in column (2) and (4) are very similar to our baseline. Dropping size in column (3) has a larger impact on the coefficient. Size as measured as the number of employees may be fixed when the variable of interest is determined. It seems likely given that a large majority of the French workers are under a permanent contract that makes redundancy not immediate.[31] Finally, in column (5), we use lagged control variables to make sure they are fixed when the variable of interest is determined. We obtain a coefficient of a similar scale although it cannot be compared directly to the baseline since the sample contain many less observations.

3.6.2 Other checks

Outlying observations

To make sure some outlying influential observations do not affect the pattern of our findings we removed the top and bottom 1% of firms in terms of main control variables. All our findings remain unchanged and the coefficients are of very similar magnitudes to those reported as the main results.

Origin of imports

Our main estimations use the share of material imports from China and India as a proxy for the average cost of inputs. In line with our theoretical motivation, we also look instead at all low-wage countries, defined as in Bernard, Jensen, and Schott (2006a) as countries with a GDP per capita which is lower than 5% of the US GDP per capita (see table 3.7, column 1, 3, 5, and 6). The share of 'material' imports from these two country groups gives results that are very similar to our main outcomes in column (2), suggesting China and India are the main drivers behind these results. Replacing China & India by all BRIC countries (China, India, Brazil , Russia, and South Africa) also provides similar results.

[31] In 2013, 77% of the French workers has a permanent contract (Insee, 2013).

Table 3.5: Share of 'material' imports from China and India and propensity to carry out environmental innovation

Dependent variable	**Importance given to material or energy saving innovation on a scale from 0 to 3**		**Equals 1 if the importance of material or energy saving innovation is not 0**	
	Ordered-Probit (1)	Ordered-IV-Probit (2)	Probit (3)	IV-Probit (4)
Share of 'material' imports from China & India in all 'material' imports	-0.002***	-0.012**	-0.002*	-0.011**
	(0.001)	(0.005)	(0.001)	(0.006)
Exporter (0/1)	0.229***	0.282***	0.262***	0.323***
	(0.054)	(0.056)	(0.061)	(0.063)
Number of sourcing countries	-0.001	0.001	-0.000	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
ln($Capital$)	0.023	0.029	0.053**	0.061**
	(0.021)	(0.021)	(0.025)	(0.026)
ln($Size$)	0.264***	0.239***	0.260***	0.234***
	(0.026)	(0.027)	(0.032)	(0.033)
ln(Labor Productivity)	0.137***	0.124***	0.064*	0.051
	(0.029)	(0.030)	(0.037)	(0.038)
Inverse Mills Ratio	0.658***	0.647***	0.677***	0.670***
	(0.030)	(0.030)	(0.028)	(0.028)
Number of observations	10,574	10,355	10,340	10,155
Number of firms	6,022	5,873	5,912	5,785
First-stage IV coefficient	-	0.492***	-	0.501***
Industry-level dummies (NACE 4 digits)	Yes	Yes	Yes	Yes
Firm fixed-effect	No	No	No	No

Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
All columns include a comprehensive set of period dummies and a constant (not reported)

Pollution intensity of products

Our main estimations use the share of 'material' imports from China and India as a proxy for the average cost of inputs. In column 3, 4, and 6 of table 3.7 we replace material goods by 'energy intensive' goods defined as fuels and products from industries covered by the EU-ETS e.g. coal, crude steel, fertilizers, etc. Results that are similar to our main outcomes in column (2) but the coefficient is higher in absolute value. It is not surprising that the disincentive effect of imports on green innovation is larger when we consider pollution intensive goods.[32]

Period average

We also check whether our choice to take only the first two years to calculate period average affects our results. When we average our regressors with the three years of the

[32]Energy intensive goods are in generally considered also as pollution intensive.

Table 3.6: Share of 'material' imports from China and India and propensity to carry out environmental innovation

Dependent variable	Importance given to material or energy saving innovation on a scale from 0 to 3				
	Ordered-IV-Probit				
	Contemporary control variables				Lagged control variables
	(1)	(2)	(3)	(4)	(5)
Share of 'product type' imports from 'low-cost' countries in all 'product type' imports	-0.012** (0.006)	-0.012** (0.005)	-0.019*** (0.005)	-0.013*** (0.005)	-0.021*** (0.008)
Exporter (0/1)	0.282*** (0.056)				0.086 (0.117)
Number of sourcing countries	0.001 (0.003)				0.010** (0.005)
ln(*Capital*)	0.029 (0.021)				-0.004 (0.038)
ln(*Size*)	0.239*** (0.027)	0.294*** (0.012)		0.218*** (0.011)	0.264*** (0.050)
ln(Labor Productivity)	0.124*** (0.030)				0.197*** (0.056)
Inverse Mills Ratio	0.647*** (0.030)	0.652*** (0.030)	0.678*** (0.030)		0.735*** (0.052)
Number of observations	10,355	10,355	10,355	10,355	3,887
Number of firms	5,873	5,873	5,873	5,873	2,120
First-stage IV coefficient	0.492***	0.492***	0.498***	0.492***	0.518***
Industry-level dummies (NACE 4 digits)	Yes	Yes	Yes	Yes	Yes

Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
All columns are estimated with Ordered-IV-Probit and include a comprehensive set of year dummies and a constant (not reported)

period, we obtain the same result as in our baseline estimation (available upon request).

Third country group used in the IV computation

In our baseline estimation, we calculate our instrumental variable based on the imports of the European member states except France. We check whether this choice affects our result by replacing all European member states except France by the U.S. Results are reported in column (5) and (6) of table 3.7 and are similar to our base estimation.

Over-reporting

There may be a concern pertaining to companies wishing to look more environmentally-friendly and thus over-reporting 'green' innovations. Since we find that the 'material' imports reduce the propensity to introduce an environmental innovation, if companies indeed over-report these innovations, then our findings would represent a lower bound of estimates.

Placebo tests

Table 3.7: Share of 'material' imports from China and India and propensity to carry out environmental innovation

Dependent variable	**Importance given to material or energy saving innovation on a scale from 0 to 3**					
	Low-cost countries					
	Low-wage	China & India	Low-wage	China & India	Low-wage	Low-wage
	Type of products					
	Material	Material	Energy	Energy	Material	Energy
	Third country used for the IV computation					
	EU	EU	EU	EU	USA	USA
	(1)	(2)	(3)	(4)	(5)	(6)
Share of 'product type' imports from 'low-cost' countries in all 'product type' imports	-0.012**	-0.012**	-0.014**	-0.016***	-0.017***	-0.014**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
Exporter (0/1)	0.270***	0.267***	0.249***	0.257***	0.143***	0.250***
	(0.068)	(0.068)	(0.068)	(0.068)	(0.034)	(0.068)
Number of sourcing countries	-0.000	-0.001	0.002	0.001	0.000	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\ln(Capital)$	0.019	0.020	0.021	0.021	0.019	0.021
	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)
$\ln(Size)$	0.276***	0.278***	0.268***	0.271***	0.269***	0.269***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)
ln(Labor Productivity)	0.144***	0.145***	0.144***	0.145***	0.143***	0.144***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Inverse Mills Ratio	0.755***	0.762***	0.734***	0.738***	0.748***	0.734***
	(0.037)	(0.036)	(0.036)	(0.036)	(0.037)	(0.036)
Number of observations	7,679	7,679	7,679	7,679	7,679	7,679
Number of firms	4,611	4,611	4,611	4,611	4,611	4,611
First-stage IV coefficient	0.502***	0.508***	0.686***	0.631***	0.202***	0.231***
Industry-level dummies (NACE 4 digits)	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors robust to heteroskedasticity and autocorrelation in parentheses $***p < 0.01, **p < 0.05, *p < 0.1$
All columns are estimated with Ordered-IV-Probit and include a comprehensive set of year dummies and a constant (not reported)

Eventually, we perform a number of placebo or falsification tests. In our main results we show that green innovation is affected by the share of 'material' imports from China and India. We thus check whether the same effect can be observed for 'material' imports from other destinations (EU or OECD). We find that the share of 'material' imports from the EU in total 'material' imports does not have a statistically significant effect on the propensity to introduce an environmental innovation in the next period.[33] Overall, these tests show that we find an effect only where we would expect to find it, i.e. when looking at products sourced from emerging economies. This suggests that the origin of imports matter for the introduction of new clean innovation.

[33]Similar results are found when considering the share of 'material' imports from the OECD in total 'material' imports. They are available upon request.

Controlling for environmental regulation There are ample empirical evidence that environmental regulation is a driver of environmental innovation. If the share of material imports from low cost countries is correlated with environmental regulations, then our base estimate has a larger bias. In Chapter 4, environmental regulation is proxied by the ratio between pollution abatement capital expenditure and total capital expenditure. At equal sample, we obtain highly similar point estimate whether environmental regulation is included as an additional control variable.[34] Since this leads to lose more than half of the observations, we do not include environmental regulation in our base specification.

3.7 Conclusion

In this paper, we combine firm-level trade and financial data with information on innovation activities to examine the impact of trade with low-cost countries on clean innovation. Our data covers close to 6,000 French companies observed from 1994 to 2010. Consistent with our hypothesis, we find robust evidence that firms importing a higher share of their material inputs from Southern countries are less likely to engage in 'clean' innovation that reduces material or energy use per unit of output. In other words, trade affects the direction of technological change. This finding is stable across various definitions of the group of countries used to define imports from Southern countries, the type of products considered, and the country used in the instrumental variable computation. Our main results focus on China and India, but our findings are robust to considering all low-wage countries. The magnitude of the effect is large: at the sample mean, an increase in the import share of 'material' products from India and China in a firm's total 'material' imports by one standard deviation (a move from 3% to 16%) is predicted to decrease the firm's propensity to engage in environmental innovation by 15 percentage points. Since the share of US imports of intermediate goods coming from China and India has gone from 2.0% in 1990 to 9.5% in 2010, this finding

[34] Results available upon request.

suggests that trade with low-cost countries might have significantly reduced environmental innovation in developed countries during the past two decades.

This paper has important policy implications. Our findings suggest that carbon leakage may not only affect jobs and emissions in the short run. It also affects long-run competitiveness by reducing incentives for firms to conduct innovation in 'clean' technologies. This may provide further justification for policies aimed at preventing 'leakage' such as border-tax adjustment.

Our work could be extended in several directions. First, an obvious limitation is that we do not fully control for unobserved heterogeneity. One way to extend our empirical investigation would be to draw upon the recent econometric literature and perform set identification under weaker identifying assumptions. So far, we do our best to control for observed heterogeneity by including many control variables, but this approach is obviously imperfect. Better data will make it possible to reduce omitted variable bias by including additional control variable such as firm competitive environment and credit constraint.

Second, data on innovation are self-reported so that some firms may not reveal their true innovation outputs. Cross-checks using patent data, that are arguably not manipulated, are useful in that situation. Nevertheless, patent data on material saving or energy saving technologies are not available yet.

Unbundling the Porter Hypothesis. Evidence from French manufacturing firms[35]

Damien Dussaux

MINES ParisTech, PSL - Research University, CERNA - Center for industrial economics

Abstract

I examine the impact of environmental regulations on firm profitability using an extensive dataset on French manufacturing firms observed from 1994 to 2010. I first investigate the overall impact of firm's abatement effort on their productivity. Then, I test whether abatement effort changes the scale and the direction of firm's innovation and whether this shift in innovation affects firm's productivity. Finally, I estimate the impact of environmental regulations on firm profitability. I find that environmental compliance costs has a small negative impact on firm profitability. Additionally, I find evidence that higher abatement effort leads to a change in the direction of innovation towards cleaner technologies but has no effect on the scale of innovation. I also find that the productivity return on R&D expenditure is lower as the share of green innovation increases. Overall, the null hypothesis that abatement effort has no significant effect on productivity is not rejected by the data based on the most robust identification strategy. These results suggest that the Porter Hypothesis does not hold but also that environmental regulations do not harm much firm competitiveness.

Keywords: Porter hypothesis, profitability, productivity, environmental regulation, green innovation.

JEL Classification: H23, O31, Q52, Q55, Q58

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Chapter 4

Unbundling the Porter Hypothesis. Evidence from French manufacturing firms

4.1 Introduction

Environmental policies are regularly accused of destroying firms competitiveness that leads to the destruction of domestic jobs. There are two opposite views. Economists in line with Porter and Van der Linde (1995) believe that properly design environmental regulation can trigger innovation that may partially or more than fully offset the costs of complying with them. In other words, environmental regulation is neutral or beneficial to firm competitiveness. In contrast, more orthodox economists think that if there was an opportunity to improve productivity, firms would have done it whether they are under the regulation or not. As a result, they believe that environmental regulations can only harm competitiveness. It is important to know if and how much environmental regulations harm the private sector. This is because, based on this belief, policy makers may be reluctant to introduce more stringent environmental regulations that could be beneficial to public health and environment and result in economy-wide benefits. So far, this question is still highly debated because of mixed empirical evidence.

This paper aims to fill this gap by implementing a new test of the Porter Hypothesis. I make the analysis in two steps. In the first step, I examine the impact of firm share of capital expenditure dedicated to pollution abatement, that is firm environmental effort mainly driven by environmental regulations, on firm productivity. I proceed in two phases. I first consider the *overall* impact of firm environmental effort on firms total factor productivity (TFP) using a new panel data set of nearly 16,000 French manufacturing firms observed from 1994 to 2010. I identify the effect of environmental effort on firm productivity using a novel instrumental variable strategy based on a matching method. In a second phase, I examine the role of green and non green innovation to provide a positive explanation of my first result. I test whether firm environmental effort changes the scale and the direction of innovation and whether this shift in innovation alters firm productivity. I employ a pooled data set of up to 10,000 French manufacturing firms that contains data on innovation. In the second step, I estimate firm profitability as a function of firm TFP and environmental regulations. I use data on compliance operating costs from a pooled data set of 5,000 firms observed in 2004 and 2010.

Using a two stage least square fixed-effects estimator on the panel data set I do not find that a higher share of capital expenditure dedicated to pollution abatement leads to lower firm TFP. Using the pooled data set, I find that firms having a higher share of capital expenditure dedicated to pollution abatement develop on average more green innovation. However, I find that the productivity return on R&D expenditure is lower as the share of green innovation increases. This result is new and the magnitude of the effect is far from being small. For instance, I find that an increase in R&D from 100,000 euros to 400,000 euros is predicted to increase TFP by 0.030 points if the share of green innovation is 25% and by 0.016 points if the share of green innovation is 50%. Finally, I find that an increase in the share of environmental expenditure in a firm's total operating expenditure by one standard deviation (a move from 0.6% to 1.6%) is predicted to decrease the firm's profitability by 0.3 percentage points. The result regarding productivity is at odds with conventional economic wisdom. It is also evidence against the Porter Hypothesis. This is because environmental regulations cannot offset compliance operating costs if they do not lead to an increase in TFP.

For the past twenty years, the Porter Hypothesis has been examined by a large number of papers (Ambec, Cohen, Elgie, and Lanoie, 2013; Dechezleprêtre and Sato, 2014). The results of these studies are highly mixed.[1] These studies vary from each other in a number of ways. First, some papers analyse regulations impact on productivity and other on profitability. Most of early studies employ country or industry-level data while recent studies tend to rely more on firm or plant-level data. Some papers analyse the effect of a specific policy while others use proxy of overall level of environmental regulation stringency. Finally previous papers do not all test the same assumptions implied by the Porter Hypothesis.

This paper makes several contributions. To the best of my knowledge, it is the first study to test jointly the different assumptions behind the Porter Hypothesis in a coherent framework. I identify five different hypotheses supported by the case studies exposed in Porter and Van der Linde (1995). First, environmental regulations trigger environmental innovation. This first hypothesis is called the "weak" version of the Porter Hypothesis in the literature (Jaffe and Palmer, 1997). Second, green innovation leads to higher productivity. Third, these regulation driven productivity gains partially or fully offset regulation compliance costs. Fourth, regulated firms develop a first mover advantage that makes them winners in the long run as foreign countries catch up with environmental regulations.[2] Fifth, Porter and Van der Linde (1995) stress that flexible policies such as market-based instruments have less adverse impact than command and control regulations on firm competitiveness. This last assumption is called "narrow" Porter Hypothesis by (Jaffe and Palmer, 1997).

Most studies analyse the overall effect of environmental regulations on productivity without analyzing the role of green innovation nor testing for dynamic effects (Gollop and Roberts, 1983; Smith and Sims, 1985; Gray, 1987; Conrad and Morrison, 1989; Barbera and Mc-

[1] Ambec, Cohen, Elgie, and Lanoie (2013) provide several explanations for these variety of results in a recent literature review.

[2] I suggest that we call this assumption the "dynamic" Porter Hypothesis.

Connell, 1990; Dufour, Lanoie, and Patry, 1998; Boyd and McClelland, 1999; Berman and Bui, 2001; Alpay, Kerkvliet, and Buccola, 2002; Gray and Shadbegian, 2003; Greenstone, List, and Syverson, 2012; Tanaka, Yin, and Jefferson, 2014). Some papers test several hypothesis at a time but not altogether. Several studies incorporate dynamics but does not include the innovation dimension. For instance, Lanoie, Patry, and Lajeunesse (2008) and Albrizio, Koźluk, and Zipperer (2014) estimate distributed lag models and Rassier and Earnhart (2015) estimate the impact of current regulation on expected profitability. Other studies incorporate the innovation dimension but no dynamic effects (Lanoie, Laurent-Lucchetti, Johnstone, and Ambec, 2011; Rexhäuser and Rammer, 2014; Leeuwen and Mohnen, 2013).

The present paper incorporates dynamics and distinguishes the effect of environmental regulations on the scale and the direction of innovation when testing the Porter Hypothesis. Although, it does not test the "narrow" Porter Hypothesis due to the proxy of environmental regulatory stringency used. As far as I know, this paper is the first to analyse the impact of environmental regulations on both productivity and profitability. This is important since profitability, which conditions firm employment and firm exit of a market, depends on productivity as well as regulations.

The second contribution of the paper lies in the empirical strategy. Regulators may impose less stringent regulations to protect firms with low TFP or low profitability. If this is the case, then environmental regulations are endogenous. I deal with this simultaneity issue between firm productivity and environmental effort by employing an innovative way to generate an instrumental variable. Few studies actually deal with the endogeneity of environmental regulations. Gray and Shadbegian (2003) employ Arellano and Bond (1991)'s difference Generalized Method of Moments estimator to instrument pollution abatement operating cost with lagged independent variables. Greenstone, List, and Syverson (2012) build a contrefactual using plants in low pollution intensive industry as "control" group. Finally, Leeuwen and Mohnen (2013) use lagged independent variables.

Another advantage of the empirically strategy is the data sets used. Unlike more aggregated data, firm-level data allows for the identification strategy to be much less sensitive to macroeconomic shocks that are correlated with country or sector level innovation and environmental regulations. The data covers the entire manufacturing sector with few exceptions. Also the sizes of the data sets used ,up to 16,000 firms observed during 15 years, are important making hypothesis testing more reliable.

The third contribution is that I test the impact of environmental regulations as a whole by using *both* environmental capital and operating costs as main independent variables. The advantage of these measure is that they summarize the multidimensionality of environmental regulations into measures comparable across firms producing in the same country. Studies focusing on a restricted set of policies cannot provide a general conclusion on the Porter Hypothesis. Moreover, identifying the effect of a specific policy poses empirical issues as one must account for other policies often correlated with the dependent variables and the policy of interest.

The paper is organized as follows. The next section describes the framework that supports the structure of the subsequent investigation. Section 4.3 lays out the identification strategy. Section 4.4 presents the data. Section 4.5 reports the base estimation results and section 4.6 shows different robustness checks. I conclude in section 4.7.

4.2 Background and Framework

4.2.1 French environmental regulations

In this section, I briefly describe the regulations applied to the manufacturing sector.[3] I voluntary exclude regulations related to mining and quarrying industries. As in other countries, the French environmental regulation is multidimensional. It can be separated in three broad categories that are resource consumption, climate change, and pollution emission.

Lands are subject to different regulatory measures. Firms must comply with the local urban plan that authorises or not new constructions based on several environmental criteria.

[3]Most of this section derives from Commissariat Général au Développement Durable (2013) .

In addition, any construction project must include an environmental impact study.[4] Furthermore, a planning tax called "taxe d'aménagement" is levied based on the surface of the new construction, a flat-rate of at least 660 euros per square meter, and a rate varying from 1% to 5% depending on the municipality. This planning tax is an implicit tax on the use of non-artificial lands. Municipalities can also choose a minimal density threshold that leads to payments if exceeded by the owner of the construction permit.

Firms must pay a fee on their water intake. The fee rate depends on the watershed, the water usage, the soil geology, the location of water resources, and the location of the intake. For instance, drinkable water is taxed more than water used for cooling. As the result, the weighted average rate vary from 4.2 euros per 1,000 m^3 in Rhin-Meuse to 26.5 euros per 1,000 m^3 in Seine-Normandie. Intake of underground water is also taxed more than intake of superficial water. An additional fee independent from the quantity of water can also be applied.

France has introduced 14 Extended Producer Responsibility (EPR) schemes to increase recycling and material saving. These EPR schemes cover a wide range of materials such as paper, end-of-life vehicles, textiles, household packaging, etcetera.[5] For each EPR, producers of goods contribute to finance a non-profit private companies in charge of managing waste flows. The contribution of the firms depends on the quantity of output they sell in the market. The financial flows generated are significant. 1.4 billion euros were collected in 2015 (French Ministry of Ecology and Energy, 2013).

As in many other countries, the French government collects taxes on fuel consumption. They consist in an excise tax which rate varies across fuels and is determined by the European directive 2003/96/CE and a VAT at 19.6% (OECD, 2013). While the primary objective of these taxes is to raise revenue, they effectively limit the consumption of fuels and the emissions associated with it. However, France makes exemptions for sectors of the manufacturing industry like many other European countries (Ekins and Speck, 1999). For

[4] Articles L. 122-1 to L. 122-3 and R. 122-1 to R. 122-16 of the French Environmental code. See http://www.legifrance.gouv.fr/content/download/1963/13739/version/3/file/Code_40.pdf

[5] There is one collective scheme for each waste flow.

instance, industries such as chemical, metallurgy, cement, non-metallic products benefit from excise exemptions or from excise tax expenditures.[6]

Green House Gas (GHG) emissions are regulated through the European Union Emission Trading Scheme (EU-ETS). The EU-ETS is a cap-and-trade system for GHG emissions that covers every EU countries as well as Iceland, Norway, and Liechtenstein. The EU-ETS entered into force in 2005. Since 2013, the cap is set at the EU level and decreases by 1.74% every year. Firms cannot emit more than a certain threshold. To meet their obligation, they can buy emission permit on the market from other firms that receive emission allowances. The scheme does not include all manufacturing industries but rather focuses on GHG intensive industries: oil refineries, steel works and production of iron, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals. In 2015, there is no carbon tax for the French manufacturing sector. Also, the fret industry is not subjected to a carbon tax either so that there is no implied carbon cost on manufacturing firms consuming fret services.

In the European Union, the major instrument regulating emissions from manufacturing firms is the Industrial Emissions Directive (IED) that aims to reduce harmful industrial emissions.The Annex I of the IED lists the economic activities that are required to obtain a permit, delivered by Member States, in order to be able to operate.[7] The IED takes the form of a command and control regulation where firms cannot emit more than a certain thresholds defined at the EU level and based on the Best Available Techniques (BAT). To ensure the enforcement of the regulation, Member Sates have to perform environmental inspections at least every 1 to 3 years.

In France, emissions are also regulated with taxes called General Tax on Polluting Activities (TGAP). In 2015, 18 air pollutants including sulphur oxide, nitrous oxide, volatile organic compounds, etcetera. are subject to the TAGP.[8] There is also an output TGAP on washing powder and lubricants products. Finally, waste storage and waste incineration are

[6]See articles 265 C, 265 bis, and 266 quinquies A of the French Customs code.

[7]In France, firms must pay a fixed fee for the grant of the permit varying from 500 to 3,000 euros and an annual fee of 400 euros to operate.

[8]The rate of the tax varies by pollutant.

also subjected to a TGAP which rate is specific to the waste flow and to the facility in charge of the waste.[9] These waste taxes are passed through the cost charged to manufacturing firms by firms in charge of waste management. Finally, firms must pay a fee when they emit water pollutants. The regulation covers suspended solids, chemical oxygen demand (COD), biochemical oxygen demand (BOD), reduced nitrogen, phosphorus, metals and metalloids, inhibitors, Adsorbable Organic Halogen (AOX), and thermal pollution. A category of stringency is attributed to each watershed components given their level of pollution. There are three categories from lax to strict. The rate of the fee varies across pollutants and across categories. For example, the 2015 per kilogram rate for COD in the Seine-Normandie watershed is 0.11 euro for the lax category, 0.13 euro for the moderate category, and 0.15 for the strict category.

4.2.2 Conceptual Framework

Figure 4-1 illustrates the conceptual framework of the following analysis. Environmental regulations taking the form of emission taxes or emission standards conduct firm to invest in abatement capital to comply and maximize their profit (a). Other things equal, more stringent regulations lead to higher environmental effort (or abatement effort) equal to the ratio between abatement capital and non abatement capital. Environmental effort is a function of environmental regulation stringency and pollution intensity. Facing identical regulations, a pollution intensive firm has to invest more in abatement capital than a less pollution intensive firm. Therefore, environmental effort should be successful at capturing *firm-specific* severity of *enforced* environmental regulations. This is one of the proxy I use for environmental regulations in the empirical strategy. Its main advantage over alternative measure of stringency is to summarize the multidimensionality of environmental regulations into a single measure.[10] However, a part of the abatement expenditure can be motivated by fac-

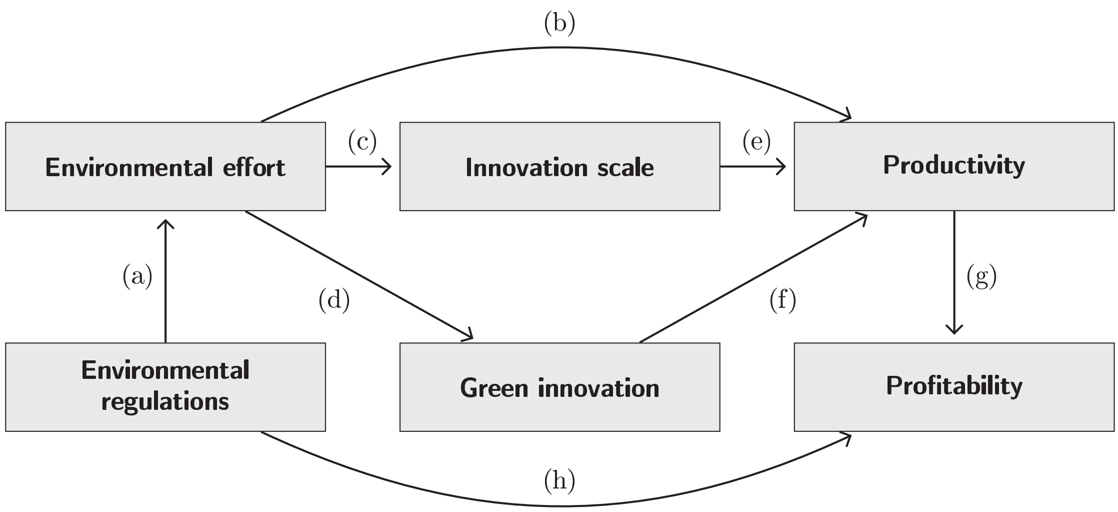
[9]See Articles 266 nonies of the French Customs code for the rate of the different TGAP.

[10]Many pollutant are targeted in different environmental media: water, air, etc. Policy instruments can be a mix of "command and control" measures such as legal emission rate and economic instruments such as emission taxes or cap and trade market. In addition, these policy instruments can be differentiated across industries. See Brunel and Levinson (2013) for a comprehensive review of the obstacles faced by researchers

tors other than regulation. Some firms may implement voluntary environmental approach because they want to avoid new regulations or they wish to win customers that have environmental preferences. Here, I assume that these other motivations are not significant when compared to compliance with environmental regulations.

Porter and Van der Linde (1995) mention case studies that illustrate two ways environmental regulations may impact a firm's technology. First, regulations could have a *direct* effect on productivity (b). Porter and Van der Linde (1995) argue that regulations cause firms to rethink their current production process. By doing that, firms may discover inefficiencies and correct them.[11] More orthodox economists argue that firms do not need regulations to rethink their production process. They do it regularly because they are rational agents. For them, regulations force firms to use capital and labour for abatement. As abatement is not productive, regulations are predicted to lower firm productivity.

Figure 4-1: Causality chain of the Porter Hypothesis



The second way environmental regulations could affect productivity is through product and process innovation. Porter and Van der Linde (1995) write "Product offsets occur when environmental regulation produces not just less pollution, but also creates better-performing

when measuring environmental regulation stringency.

[11]Porter and Van der Linde (1995) write "...the actual process of dynamic competition is characterized by changing technological opportunities coupled with highly incomplete information, organizational inertia and control problems reflecting the difficulty of aligning individual, group, and corporate incentives."

or higher-quality products, safer products, lower product costs, ...". They argue that environmental regulations conduct firms to innovate more (c) but also that these innovations reduce environmental impacts (d). They imply that some green innovations lead to productivity gains (f).[12] The fact that more innovation in general produces productivity gains is generally accepted (e). Again, orthodox economists argue that firms invest in R&D expenditure to develop new innovations in the hope to lower their production costs even in the absence of regulations. Environmental regulations may change the direction of the innovation towards greener technologies. However, green innovations may not always lead to productivity gains.

Porter and Van der Linde (1995) also claim that the way environmental regulations affect productivity is dynamic and not necessarily static. First, innovations take time to be developed. Second, green innovations may not be profitable in the short run but may provide a early-mover advantage if the regulation stringency of competitors catches up with domestic environmental regulations.[13]

In the end, firm profitability matters more than firm productivity because the former conditions firm growth and exit of the market.[14] Firm employment depends on how well the firm is doing. More productive firms are more profitable other things equal (g). However, a firm's profitability depends on its own productivity level but also on the productivity level of the other firms competing in the same market. Environmental regulations may impact profitability directly and not only through its potential effect on productivity (h). In maximizing their profit, firms may choose to pay environmental taxes on their remaining pollution emissions because it is less costly than to abate all emissions.[15] Porter and Van der Linde (1995) acknowledge the negative impact of these taxes on profitability but their hypothesis is that there are productivity gains from (a) to (g) that offset the direct negative impact of regulations on profitability (h).

[12] Porter and Van der Linde (1995) illustrate this with the example of the U.S. Clean Air Act which forbids firms to use ozone-depleting chlorofluorocarbons (CFCs) in their production processes. They mention Raytheon that adopted a new cleaning agent as substitute to CFCs. It appears that this substitution reduced production costs since the new cleaning agent could be reused.

[13] Porter and Van der Linde (1995) write "World demand is moving rapidly in the direction of valuing low-pollution and energy-efficient products..."

[14] Although firm profitability is only one of the criteria of economic performance.

[15] It is usually assumed that the marginal abatement cost is increasing.

In the next section, I analyse the plausibility of the Porter assumptions by estimating these relationships for firms in the French manufacturing sector. Finding $(a) \times [(b) + (c) \times (e) + (d) \times (f)] \times (g) + (h) \geq 0$ would provide support for the Porter Hypothesis.

4.3 Empirical Strategy

4.3.1 Environmental effort and productivity

Model specification

In this paper I empirically test whether environmental effort has an *overall* impact on productivity. This overall impact is represented by $(b) + (c) \times (e) + (d) \times (f)$ in the conceptual framework of section 4.2. I use the following linear model to estimate firm's productivity at year t conditional on some covariates:

$$\ln(TFP_{it}) = \delta'(L)ENV_{it} + \beta_1 X_{1it} + \beta_2 X_{2jt} + \alpha_i + \theta_{kt} + \alpha_0 + U_{it} \tag{4.1}$$

where $\ln(TFP_{it})$ is the economic performance of the firm i producing in the industry j at year t and is measured either by $total\ factor\ productivity$ or by $operating\ margin$. I compute TFP using the index number method. More specifically, TFP is computed as follows:

$$\ln(TFP_{it}) = \ln(OUTPUT_{it}) - \alpha_{ilt} l_{it} - \alpha_{ikt} k_{it} - \alpha_{imt} m_{it} \tag{4.2}$$

where $OUTPUT_{it}$ is the output produced by firm i and is proxied by firm's turnover, l_{it} is the logged amount of labour used in production measured in total working hours, k_{it} is the logged amount of capital used in production measured by firm's book net assets, and m_{it} is the logged amount of material used in production proxied by total expenditure in materials. The α_{it} are the input elasticities. I assume that firms minimize their production cost and that they face no adjustment costs in inputs. Under these assumptions, the input elasticities equal input cost shares.[16]

As stressed by Greenstone, List, and Syverson (2012), productivity reflects the efficiency of the firm; that is, given the inputs being used, does higher environmental effort due to environmental regulations modify how effectively the firm converts these inputs into outputs. Total factor productivity has a direct impact on firm's production cost, output, export, and profit but also on other competitiveness dimension such as employment. Accordingly, results on total factor productivity have a clear economic interpretation.

I favour the use of index numbers over the main alternative method to measure TFP that is the estimation of the production function for three reasons. First, index number does not impose a specific functional form for the production function. Second, it is difficult to identify idiosyncratic productivity parameter when estimating a production function because of several endogeneity issues.[17] Third, the index number method is much more transparent and tractable and makes study replication easier. Section 4.4.1 provides the methodology, the data source, and the descriptive statistics for the TFP variable.

In this paper, the main variable of interest is the share of 'green' investment in total firm investments, which proxies for the environmental effort (ENV) made by the company. The stricter the regulation faced by the firm, the higher the environmental effort other things equal. Here, green investments include investments in end-of-pipe technologies as well as integrated technologies to protect the environment. Capturing environmental regulation stringency with Pollution Abatement Costs and Expenditure data is far from new. Assuming that most of the effort is regulation driven is not a strong assumption. Some studies use, as we do, pollution abatement capital costs (Crandall, 1981; Barbera and McConnell, 1990; Jaffe and Palmer, 1997; Dufour, Lanoie, and Patry, 1998; Lanoie, Patry, and Lajeunesse, 2008). Many studies use instead pollution abatement operating costs (Gray, 1987; Nelson, Tietenberg, and Donihue, 1993; Brunnermeier and Cohen, 2003; Gray and Shadbegian, 2003).

[16]This approach is also adopted by Greenstone, List, and Syverson (2012). See Syverson (2011) for more details about TFP computation.

[17]These problems are numerous (Olley and Pakes, 1996). The unobserved idiosyncratic parameter is correlated with the input choices. Input are endogenous because chosen at the same time as output. The firm error terms are serially correlated. Entering and exiting firms can generate a selection bias.

Jaffe and Palmer (1997) argues that capital costs capture shocks to regulation compliance better than operating costs since the latter contain the cost of capital expenditures in the smoothed form of yearly depreciation. Levinson (1996b) favours operating costs and argues that most capital costs will be incurred by new construction and more new construction will therefore have higher abatement capital expenditures. Levinson (1996b)'s argument developed for environmental stringency at the U.S. state level is also valid at the firm level. To solve this problem, we divide green investment by total investment to control for firm overall propension to invest. This supresses the endogeneity problem arising from the omission of firm overall propensity to invest in the model. Similarly, Dufour, Lanoie, and Patry (1998) and Lanoie, Patry, and Lajeunesse (2008) calculate the ratio between pollution abatement capital expenditures and total cost at the industry level. Section 4.4.2 provides the data source and descriptive statistics for environmental effort.

$\delta'(L)$ is a vector polynomials in the lag operator. To test the Porter Hypothesis, we include several lags of our proxy of environmental effort to capture dynamic effects. The PH states that "properly designed environmental regulation can trigger innovation that may partially or more than fully offset the costs of complying with them" (Porter and Van der Linde, 1995). There are now several evidence that environmental regulations spur environmental R&D expenditures and environmental innovation (Rehfeld, Rennings, and Ziegler, 2007; Veugelers, 2012; Aghion, Dechezleprêtre, Hemous, Martin, and Reenen, 2012; Ambec, Cohen, Elgie, and Lanoie, 2013). However, innovation is not necessarily a short term process. It can take several years to develop a technology in response to past environmental regulation and that will affect current profit. Finding a positive long run multiplier is an evidence in favour to the Porter Hypothesis. Studies looking only at contemporaneous relationship may lose the positive or negative impact of past environmental regulation on current economic performance. The other advantage of using the distributed lags of environmental regulation is that we capture all the canal by which current and past environmental regulation could affect current profit. Looking at innovation as being the unique mediator between past environmental regulation and current profit may be too restrictive. Dufour, Lanoie, and Patry

(1998) and Lanoie, Patry, and Lajeunesse (2008) also use lags of environmental regulation in their empirical strategy. In this paper, we test several lag structures.

I include a number of firm level controls in X_1 that include firm financial independence and firm age. Firm *financial independence* is measured as the ratio between equity and total liabilities and aims to capture firm access to credit. Muûls (2008) finds that financial independence have the highest beta coefficient as a regressor of firm credit constraint. We include financial independence as a control variable because firms having credit constraint are less able to do environmental effort or any actions such as investing in R&D that might raise their productivity. We include firm *age* as a control since it can be correlated with both productivity and environmental effort. Old firms may be more productive other things equal because of learning by doing. Grandfathered environmental regulations that require only new firm to comply with environmental standard may lead old firms to invest less in pollution abatement capital.

I also include a number of industry level controls in X_2 that include industry exposure to international competition and industry concentration because they may be correlated with both the dependent variable and environmental effort. According to Syverson (2011) high competition can induce firms to take costly productivity raising actions.[18] The intensity of the competition within an industry depends on intra-market concentration and on its exposure to foreign markets. Firms producing in a highly concentrated industry have less incentive to raise their productivity. Olson (2009) demonstrates that the smaller the lobbying group, the more efficient it is at influencing policy makers. Therefore concentrated industry may face less stringent environmental regulations. Here, I capture *industry concentration* with the normalized Herfindahl-Hirschman Index computed at the 3 digits level of the NACE 2 classification. If an industry is exposed to foreign competition, policy makers may be less stringent and cause lower environmental effort other things equal advocating the protection of domestic jobs. Here, I measure *exposure to foreign competition* as the ratio between total import value and domestic output value at the 3 digits level of the NACE 2 classification.

[18] See for instance Bernard, Jensen, and Schott (2006b), Van Reenen (2011), Lelarge and Nefussi (2013), and Bloom, Propper, Seiler, and Van Reenen (2015).

Finally I employ firm-level fixed effects to control for any time invariant firm caracteristics α_i that could be correlated with the dependent variable and the regressors. A comprehensive set of sector $\times$ year dummies is included to control for any time varying sector specific shocks θ_{kt} such as productivity spillovers, sector deregulation or the flexibility of input markets that may affect firm productivity and environmental effort.[19] There are other time varying firm-level factors such as managerial talent, firm reputation, or loyal consumer base that can affect productivity and are included in U_{it}. I assume that these factors are not correlated with environmental effort. Section 4.4 provides greater detail on the data and the variables used in the estimations.

Endogeneity issues

Estimating equation (4.1) with the OLS fixed effects estimator could still produce biased estimates because of the endogeneity of the environmental effort variable. First, there could still be other factors in the error term that are correlated with firm environmental effort. Second, there could be reverse causality if firm productivity causes change in firm environmental effort. Authorities may introduce less stringent regulations in a particular industry if they observe that the productivity of this industry is low. This kind of situation is in fact intended in the IED. EU Member States can set less strict emission limit values if they show that the emissions levels associated with BAT lead to disproportionately high cost given a particular situation. To tackle these endogeneity issues, I estimate equation (4.1) using a Two Stage Least Square (TSLS) fixed effects estimator.

I use the environmental effort ($SIMENV$) made by a similar firm that is not competing on the same market as the firm observed as an instrumental variable. I assume that firms that belong to the same sector in have similar technologies.[20] As a result, they will adapt their environmental effort in a similar manner to exogenous shocks, especially if they have similar other characteristics. If this assumption holds, ENV and $SIMENV$ should be correlated.

[19] I use the 2 digits level of the NACE 2 classification for this set of sector dummies.

[20] The definition of an economic sector is the first two digits of the Statistical Classification of Economic Activities in the European Community or NACE nomenclature.

Because, we select a similar firm that is not competing on the same market, $SIMENV$ should not be correlated with $ECONPERF$ ensuring the validity of the instrument.[21]

For each pair of firms (i, l), we compute a matching score based on a vector of K observed characteristics C_k:

$$SCORE_{ilt} = 1 - \frac{1}{K}\sum_{k}\frac{|C_{kit} - C_{klt}|}{C_{kit} + C_{klt}} \tag{4.3}$$

The C_k are positive numbers so that the matching score varies from 0 to 1. $SCORE_{ilt} = 1$ if $C_{kit} = C_{klt}, \forall k$. $SIMENV$ is the ENV of the nearest neighbour, the firm j having the highest matching score with the firm i. In our baseline specification, we include in X the total number of employees ($SIZE$), the firm's net assets ($CAPITAL$), and the energy intensity ($ENERGYINT$). We test the sensitivity of our results by employing different versions of our instrumental variable using a different vector C and using more than one neighbouring firms.

4.3.2 Environmental effort, scale and direction of innovation

Porter and Van der Linde (1995) claim that properly design environmental regulations trigger innovation. This part of the Porter Hypothesis has been called the weak version of the Porter Hypothesis. Here, I present the identification strategy to test whether environmental effort change the scale or the direction of the innovation. I start to estimate relationship (c) in the conceptual framework of section 4.2. I use the following model to estimate firm's R&D expenditure at period p conditional on some covariates:

$$R\&D_{ip} = f(\gamma'(L)ENV_{ip} + \beta_3 X_{1ip} + \beta_4 X_{2jp} + \alpha_i + \theta_{kp} + \alpha_0 + V_{ip}) \tag{4.4}$$

where $R\&D_{ip}$ is firm total expenditure in research and development. R&D is usually seen as a an input for innovation and captures innovation effort rather than innovation achievement. The latter is usually captured by a dummy equal to one when firms respond that they

[21] The definition of a market is the four digits of the Statistical Classification of Economic Activities in the European Community or NACE nomenclature.

developed at least one new innovation. Here, I use R&D expenditure as a proxy for the size of the technological contribution of the new innovations developed by the firm. Although not all investment spend in R&D gives birth to a new innovation, R&D expenditure is likely better at capturing the technological contribution of the new innovations better than a mere innovation dummy.

As $R\&D_{ip}$ takes only on positive or null integers, we use a Poisson model for equation (4.4) so that $f(.)$ is the exponential function. In the base estimation, I employ the Poisson Maximum Likelihood (PPML) estimator proposed by Silva and Tenreyro (2006) who evaluate the small sample properties of competing estimators for the gravity equation. They find the PPML estimator outperforms the log linear model under different scenarios of heteroskedasticity. The major advantage of the PPML estimator over the log linear estimator is that it takes into account that the dependent variable can take the value zero in an important number of cases and positive integer in the others. The log transformation of the dependent variable leads to select only firm engaging R&D expenditures and results in obtaining biased estimates.

Then, I estimate relationship (d) in the conceptual framework of section 4.2. I use the following linear model to estimate firm's share of green innovation at period p conditional on some covariates:

$$GREENINNOV_{ip} = \rho'(L)ENV_{ip} + \beta_5 X_{1ip} + \beta_6 X_{2jp} + \alpha_i + \theta_{kp} + \alpha_0 + \epsilon_{ip} \tag{4.5}$$

where $GREENINNOV_{ip}$ is the share of green innovation of firm i at the period p. In the CIS questionnaire, firms are asked to qualify the effect of the innovations they introduced. The innovations can have 9 different effects such as "increasing the range of goods or services" and "improving the quality of goods or services". The list of effects is presented in table 35 of the appendix. Two of these effects are environmental: "reducing materials and energy per unit of output" (ECO) and "reducing environmental impacts or improved health and safety" (EXT). Firms are asked to assess the degree of importance of each of these effects. The degree of importance of the effects can be "not relevant", "low", "medium", and "high". I associate a score of 0 when the firm answers that the effect is "not relevant", 1 if the answer is "low importance", 2 if the answer is "medium importance", and 3 if the answer is "high importance". Then I calculate the share of green innovation as follows:

$$GREENINNOV_{ip} = \frac{D_{ECO,ip} + D_{EXT,ip}}{\sum_k D_{kip}} \tag{4.6}$$

where D_{kip} is the numerical degree of importance of the effect k.

For both equations (4.4) and (4.5), I use the same control variables as in section 4.3.1 and I add the size of the firm as an additional control because large companies tend to spend more in R&D expenditure. As explained in the data section 4.4.3, the CIS data set used in this section differs from the data set used in section 4.3.1. A very few number of firms respond more than once to a CIS wave. This makes the first differencing estimator and the fixed effects estimator innapropriate to identify equation (4.4) and equation (4.5). However, I believe that the control variables are successful in capturing firm heterogeneity.

4.3.3 Green innovation and firm productivity

That innovations triggered by environmental regulations allow firms to offset the costs of complying with the regulations is an assumption implied by the Porter Hypothesis. In this section, I test whether developing green innovation is associated with higher productivity. This corresponds to relationship (f) in the conceptual framework of section 4.2. I use the following linear model to estimate total factor productivity of firm i at period p conditional on some covariates:

$$\begin{aligned} \ln(TFP_{ip}) =& \tau_1 R\&D_{ip} + \tau_2 GREENINNOV_{ip} + \tau_3 R\&D_{ip} \times GREENINNOV_{ip} \\ &+ \beta_7 X_{1ip} + \beta_8 X_{2jp} + \alpha_i + \theta_{kp} + \alpha_0 + \upsilon_{ip} \end{aligned} \tag{4.7}$$

where $\ln(TFP_{ip})$ is logged total factor productivity of firm i as measured in section 4.3.1, $R\&D_{ip}$ is the R&D expenditure, and $GREENINNOV_{ip}$ is the share of green innovation. I include an interaction term between $R\&D_{ip}$ and $GREENINNOV_{ip}$ to capture the fact that the share of green innovation may alter the productivity return of R&D expenditure. Note that relationship (f) presented in section 4.2 is estimated via coefficient τ_1.

I use the same control variables as in section 4.3.1. As explained in the data section 4.3.2, the first differencing estimator and the fixed effects estimator inappropriate to identify equation (4.3.3) since few firms answer more than once the CIS questionnaire. Nevertheless, I believe that the control variables are successful in capturing firm heterogeneity.

4.3.4 Compliance operating costs and firm profitability

In this section, I estimate the impact of compliance operating costs on firm profitability that corresponds to the (h) arrow in figure 4-1. To do so, I employ the following linear model:

$$OPMARG_{it} = \delta \ln(COMPLY_{it}) + \gamma \ln(TFP_{it}) + \beta X_{it} + \theta_k + \lambda_t + \alpha_0 + \xi_{it} \tag{4.8}$$

where $OPMARG_{it}$ is the operating margin of firm i at year t. It is defined as the ratio between gross operating profit and turnover. This is similar to the approach adopted by Rexhäuser and Rammer (2014) and Rassier and Earnhart (2015) who use firm return on sales. We choose operating margin because it equals return on sales after several taxes including environmental taxes. In contrast, looking at return on sales implies missing one of the effects of environmental regulations on firm economic performance. Dividing the absolute profit by the turnover ensures that any omitted regressor that is correlated with firm turnover does not automatically contaminate the error term and generate endogeneity. Section 4.4.1 provides the methodology, the data source, and the descriptive statistics of these economic performance variables.

$\ln(COMPLY_{it})$ is the logged share of environmental expenditure and aim to proxy environmental policy stringency. This share equals the ratio between operating expenditure to protect the environment and firm's turnover.[22] The numerator include expenditure due to the operation of abatement capital, expenditure due to environmental taxes and expenditure due environmental management such as training of environmental manager or the purchase

[22] Note that the numerator has only positive value in the estimation sample.

of environmental consultancy services. These operating expenditure exclude expenditure for labour health and security and expenditure that allows the reduction of material or energy use.

$\ln(TFP_{it})$ is logged total factor productivity of firm i as measured in section 4.3.1. It captures the technology level of the firms and should have a positive impact of firm profitability. Firm profit function depends not only on technology but also on input prices. X_{it} contains a number of firm-level control variable. I proxy the price of labour by the ratio between wages paid to the employee and firm total number of employee. I use financial independence to control for the price of capital. Firms that are financially independent can obtain credits at a lower rate. Finally, I include the logged market share of firms i in its 3-digit NACE 2 industries j in order to capture market power as Rexhäuser and Rammer (2014) and Rassier and Earnhart (2015). Firms with high market power extract more profit because they can influence market prices.

Firms provide this value only for two years, 2004 and 2010, which makes using fixed effect estimators not possible. Therefore, I include one lag of the dependent variable as an additional regressor to account for historical factors that cause current differences in the dependent variable and that might be correlated with $\ln(COMPLY_{it})$. Finally, I include a comprehensive set of sector dummies θ_k and a time dummies λ_t equal to 1 when the year is 2004. I estimate equation (4.8) with OLS.

4.4 Data

In this paper, I use two different data sets. The first is an unbalanced panel data set of 16,000 French manufacturing firms observed each year from 1996 to 2011. The panel data set is a composite of two data sets: a survey on firms investment to protect the environment named Antipol and a financial data set both described below. I use this panel data set to estimate equation (4.1) in section 4.3.1 and equation (4.8) in section 4.3.4. The second data set is a pooled data set of 7,500 French manufacturing firms observed during four periods of three years each from 1998 to 2008.[23] This pooled data set is a composite of three data sets: the Antipol data set, the financial data set, and the Community Innovation Survey. I employ the pooled data set to estimate equation (4.4), equation (4.5), and equation (4.7). Below we describe each of the data sets in turn.

4.4.1 Financial data

The financial data on manufacturing firms come from two main data set. The first is the Unified and Comprehensive File of SUSE (FICUS) database. FICUS is based on an annual fiscal census of manufacturing, mining and utilities firms called Unified Corporate Statistics System (SUSE). SUSE is conducted by the French Ministry for the Economy and Finance at the firm level.[24] SUSE covers all firms that are under the (industrial and commercial benefit) BIC tax system or under the (non commercial benefit) BNC tax system. Simply, SUSE covers all firms that send their tax return to the French Ministry for the Economy and Finance.

The FICUS data set on manufacturing firms provides an unbalanced panel covering over 3 millions firms for a maximum of 14 years for the 1994-2007 period. Three kinds of variables are available. First, there are firm information such as primary industry classification (at 2-4 digit NACE level), head office address, employment (measured as total employed), date of creation, etcetera. Second there are profit and loss account (income statement) variables such as total turnover, export, total labour costs, total gross earnings, etcetera. Finally, there are balance sheets variables such as the stock of capital, debt, etcetera.

The second data set for financial data is the Annual business survey (EAE) on the manufacturing industry.[25] In contrast with SUSE, it is not a census but a statistical source.

[23] Data are not available for the period 2000-2002 because the Community Innovation Survey was not undertaken at that period.

[24] For more information on this and other data sets described here, see the web-site of the French National Institute of Statistics and Economic Studies at `http://www.insee.fr/en/methodes/default.asp?page=sources/ope-enq-suse.htm`.

[25] For more information on this and other data sets described here, see the web-site of the French National Institute of Statistics and Economic Studies at `http://www.insee.fr/en/methodes/default.asp?page=definitions/enquete-annuelle-entreprises.htm`.

Firms having at least 30 employees or a annual turnover of at least 5 millions euros must reply to the survey. However, the other manufacturing firms are randomly sampled. The EAE data set on manufacturing firms provides an unbalanced panel covering on average 21,000 firms accounting for 2,9 millions of workers. The EAE data set contains almost the same variables as FICUS. For the period 1994-2007, we merge EAE and FICUS and keep data of the latter when the data for a firm is available in both data sets because FICUS is a census and thus considered as more reliable. To obtain data for 2008, 2009, and 2010 we use the FARE file, the data set that replaced both EAE and FICUS from 2008.[26]

We use the fiscal data set composed by FICUS, EAE, and FARE to compute total factor productivity, operating margin, and control variables for observed firm-level characteristics and industry-level characteristics. Table 32 shows the estimation results for two regressions. The first is the regression of logged TFP on a trend variable and on a comprehensive set of 2 digits sector dummies. The coefficient of the trend is positive and significant at the 1% level. It suggests that on average TFP increases over the years. It means that the technology used by the firms increases over time. The sector dummies point estimates are significant. The coefficient vary much from one another suggesting that productivity varies substantially between industries. These results are consistent with previous studies (Syverson, 2011). The second estimation regress operating margin on the same regressors. The coefficient of the trend is negative and significant at the 1% level. The average profit of French firms is decreasing over time. The various coefficients of the sector dummies indicate that profit varies significantly across sectors.

In figure -3 and figure -4 , I plot the point estimates of year dummies coefficient from two OLS fixed-effects estimations. Figure -3 corresponds to the a regression of logged TFP on year dummies as only regressors where the base year is 1996. Overall, the point estimates increase over time. This result that TFP increases over the years on average is consistent with the first regression reported in table 32. Figure -4 corresponds to the a regression of operating margin on year dummies as only regressors where the base year is 1996. Here, the

[26]FARE stands for Approached File of ESANE Results. ESANE stands for Annual Business Statistics Production. No web page in English exist at the time we write this paper.

point estimates decrease over time. This is further evidence that the profit of French firms has been decreasing during the last fifteen years.

4.4.2 Compliance operating and capital costs data

We use the Antipol survey to construct environmental effort at the firm level. The survey asked about 10 thousand plants about their investment in pollution control capital. Until 2005, the survey was a census for plant having at least 100 employees whatever their activities. This threshold goes down to 50 or 20 employees for pollution intensive activities. After 2006, Antipol is a census for plants having at least 250 employees and a survey for other plants stratified by activity and by size group. Antipol asks plants how much they invest in end-of-pipe technologies and integrated technologies to prevent the emissions of 7 pollutant categories: waste water, non radioactive waste, air and climate pollutant, noise and vibration, land and water pollutant, biodiversity and landscape, and other pollutants. This disaggregation level may incite plants to report their investment more carefully. Another advantage of the survey is that it explicitly excludes workplace health, security, and hygiene questions and focus exclusively on pollution control.

I aggregate these plant-level data at the firm-level because firm is the unit of observation in my empirical strategy. I start by summing end-of-pipe and integrated investment across all pollutant categories at the plant-level. Firms having no plant appearing in Antipol are dropped from the estimation sample. In addition, I assume that the pollution abatement capital expenditures of plants absent from the Antipol survey are equal to zero or very small in comparison to reporting plants. I implement robustness test in section 4.6.1 to check whether this assumption has an impact on the main results.

I combine these data on green investment with total investment provided by the financial data set described above to compute environmental effort defined as the ratio between pollution control capital investment and total capital investment at the firm level. The average environmental effort in 2006 is 4.3% but the distribution has a highly positive skew. For the same year, I find that 55% of the firms do not invest in pollution control capital while only

5% of the firms invest more than 25% of their capital in pollution control.[27]

In table 33 I report the estimation results of the regression of environmental effort on firm size, trend, and a comprehensive set of sector dummies.[28] The estimated coefficients of the firm size and trend are both negative and significant. Therefore, small firms do more environmental effort on average. Also, I find that on average environmental effort is decreasing by 0.2 percentage points between 1996 and 2011. The coefficients of the sector dummies illustrate the heterogeneity of environmental effort across sectors. Environmental effort is relatively high in textiles, other non-metallic products, electrical equipment, chemicals, and basic metals while it is relatively low in repair and installation of equipment, motor vehicles, furnitures, other manufacturing, energy distribution, and machinery. This result is consistent with the fact that pollution intensive sectors are expected to do more environmental effort at a given level of environmental policy stringency.[29]

4.4.3 Innovation data

The Community Innovation Survey (CIS) data set contains survey data and covers only a fraction of the population of French firms present in our other data sets described below. The CIS asks French firms about their activity in terms of product and process innovation, R&D, cooperative behaviour in research and innovation alliances over the last three years before the survey. The waves covering the years 1994 to 2008 include a set of questions on environmental innovation.[30] For each wave, the survey asks firms to assess the importance of the innovation effects.[31] On a total of 9 effects, 2 effects are related to the reduction of environmental externalities. Firms have four exclusive choices to qualify these effects: 'not

[27] I choose 2006 because it has the highest number of firms. The shape of the distribution does not vary much over the years

[28] This regression bears no claim about any causal effect. It is only used as a tool to produce descriptive statistics.

[29] In France, emission tax level are the same for all manufacturing industries except waste management activities. Therefore, pollution intensive firms have to do more environmental effort to comply with environmental regulations.

[30] Note that there was no survey for 1996-1998 and 2000-2002.

[31] The list of effects is presented in table 35 of the appendix.

relevant', 'low importance', 'medium importance', and 'high importance'. We translate the answer into a discrete score from 0 to 3 as explained in section 4.3.2.

The survey question about environmental innovations takes a different form for the 2006-2008 wave. Instead of being asked how important are the effects "reducing materials and energy per unit of output" and "reducing environmental impacts or improving health and safety" of the innovations developed, firm were asked whether they had introduced 6 kinds of environmental innovation: reducing material use per unit of output (ECOMAT), reducing energy use per unit of output (ECOEN), reducing CO_2 production (ECOCO), replacing materials with less polluting or hazardous substitutes (ECOSUB), reducing soil, water, noise or air pollution (ECOPOL), and recycling waste, water, or materials (ECOREC). Firms' answers are coded into binary variables equal to 1 when the environmental innovation is introduced and equal to 0 otherwise. To calculate the share of green innovation as in section 4.3.2, I approximate the scores $D_{ECO,ip}$ and $D_{EXT,ip}$ for the 2006-2008 period as follows:

$$D_{ECO,i,2006-2008} = 3 \times \frac{(ECOMAT_i + ECOEN_i)}{2} \tag{4.9}$$

$$D_{EXT,i,2006-2008} = 3 \times \frac{(ECOCO_i + ECOSUB_i + ECOPOL_i + ECOREC_i)}{4} \tag{4.10}$$

where $ECOMAT_i$ and the other right-hand side variables are dummy variables. As a result, $D_{ECO,i,2006-2008}$ and $D_{EXT,i,2006-2008}$ are bounded between 0 and 3 as for the other periods. To check whether this methodological choice influences the base estimation results I estimate the different models without the 2006-2008 wave. I get very similar result.

From the estimation sample, I find that the average share of green innovation is 20% for the 2002-2004 period. 65% of the firms have their share of green innovation between 0 and 25%, 34% of the firms have this share between 26% and 50%, and 1% of the firms have this share superior to 50%. The density of the share of green innovation is plotted in figure -6 of the appendix. The shape of the distribution is similar for the other periods of observation.

For the 2002-2004 period, I find that the average amount of R&D expenditure is 5.4 million euros while the median is 0.2 million euros. A majority of firms (13%) declare that they R&D expenditure is null for that period while 24% of the firms report they spend more than 1 million euros. Figure -7 of the appendix shows the percentage of firms for different brackets of R&D expenditure.

4.4.4 Energy consumption data

In section 4.3.1, I use energy intensity to match firms to obtain an instrumental variable. It is equal to the ratio between firm net energy consumption and firm turnover. Data come from the Annual Survey on Energy Consumption in the Industry (EACEI) produced by Insee. A part of this survey is a census for particular groups of firms. Firms having at least 20 employees and operating in either the manufacture of cement, or the manufacture of lime and plaster or the manufacture of other construction products, firms having at least 250 employees, and firms having at least 10 employees in the manufacture of industrial gases. Firms having between 20 to 249 employees are randomly surveyed. Data are available at the plant level. I use the same methodology of aggregation employed for abatement capital data.

4.4.5 Industry-level import data

In section 4.3 I use the ratio between industry-level import and industry-level domestic production to proxy industry exposure to international competition as a control variable. To compute import at the 3 digits level of the NACE 2 classification, I use bilateral trade data from BACI, the trade database developed by the CEPII.[32] Correspondence tables are used to allocate one 4 digits NACE 2 code to every product code defined at the 6 digits level of

[32] BACI is built upon the United Nations COMTRADE database and reconciles the declarations of importing countries and exporting countries. See `http://www.cepii.fr/PDF_PUB/wp/2010/wp2010-23.pdf` for more details.

the Harmonized Commodity Description and Coding System (HS). I calculate the sum of shipment value exported towards France at the 3 digits level of the NACE 2. To compute 3 digits industry-level domestic production, I calculate the sum of firms turnover from the census data described above. Table 34 shows the exposure to international competition by 2 digits sector for the 1996-1998 period and for the 2005-2007 period. Two conclusions arise from the table. First, some sectors such as food, textiles, and refined petroleum products are highly exposed to international competition while import value is low compared to domestic production for the other sectors. Second, the exposure to international competition rises for almost every sector from 1996-1998 to 2005-2007. These facts illustrate that it may be important for identification to control for such time-varying heterogeneity.

4.4.6 Estimation sample and descriptive statistics

To obtain the panel data set, I match the financial data set with the Antipol data set and the import data set. The match yields a total of 54,402 observations consisting in 16,000 French manufacturing firms observed each year from 1996 to 2011. The panel is unbalanced and the average number of years per firm is 3.5. Table 26 provides the descriptive statistics for this panel data set when estimating equation (4.1) while table 30 provides the descriptive statistics for this panel data set when estimating equation (4.8). To obtain the pooled data set, I convert the yearly financial data, the Antipol data, and the import data into periods of three years each. This allows to match these data with the CIS data available only at the three years period level. To go from year-level data towards period-level data, I calculate the average of the year-level data for the first two years of the three years period. I do not use the three years to avoid the last year of period p to overlap with the first year of period $p+1$.[33] Up to 11,049 observations are obtained from matching the pooled data sets. The resulting sample consists in 7,573 firms oberved 1.5 year on average. Table 27, 28, and 29 provides the descriptive statistics for this pooled data set depending on the equation estimated. It

[33] By running the estimations on a three year average, I get similar results. Therefore, the base results are not sensitive to this methodological choice.

is important to note that some firms are dropped because one of the two years needed to calculate the average for the control variables is missing.

Table 22 in the appendix provides the list of the sectors covered in the two data sets. On the 30 sectors, five sectors industries represent less than 1% of the firms in the panel data set. This number equals eight for the pooled data set. The remaining sectors are relatively well represented in the data. Table 25 in the appendix presents a full list of variables used in this analysis and their definitions.

4.5 Estimation results

4.5.1 Environmental effort and productivity

Estimation results of equation (4.1) are presented in table 4.1. Columns 1-4 show estimated coefficients and standard errors when the dependent variable is total factor productivity. Column 1 presents our base results from the TSLS estimation. The coefficient of environmental effort is positive but not statistically different from zero. The Kleibergen-Paap LM statistics indicates that the instrumental variable is relatively strong.[34] Column 2 displays the OLS estimation results of the same model as column 1. The coefficient of environmental effort is negative and the null hypothesis that it is equal to zero is not rejected by the data. Column 3 shows the OLS estimation of equation (4.1) when one lag of the environmental effort variable is included. The Student tests indicate that neither current environmental effort nor past environmental effort has a significant effect on firm productivity. The same result is found in column 4 where a lag of the dependent variable is included as an additional regressor. As expected, financial independence has a positive effect on total factor productivity. The age of the firm has a positive although not significant effect on productivity. Finally, I find that trade competition and industry concentration have no significant effect on productivity. This is probably due to the industry $\times$ year dummies that capture already well these two factors.

[34]The first stage estimation results of the TSLS estimation are reported in table 38 of the appendix

In summary, I find that neither current nor past environmental effort have a significant effect on firm productivity. This result is robust to the use of different estimators and lag structure specification. This is evidence that the Porter Hypothesis does not hold but it is also evidence against the argument that environmental regulations harm firm competitiveness. The next sections present the results about the potential role of green innovation inside this causality chain.

4.5.2 Environmental effort, scale and direction of the innovation

Column 1 and 2 of table 4.2 presents the PPML estimation results for the effect of environmental effort on the scale of innovation. In column 1, I estimate equation (4.4) without any lag of the environmental effort variable. In column 2, I include one lag of this variable of interest. For both model, I find negative coefficients but I fail to reject the null hypothesis that the coefficients of current and past environmental effort equal zero. The sign of the coefficients corresponding to the logged number of employees and to the industry concentration are consistent with the theoretical arguments detailed in section 4.3.2. However, the negative coefficient of trade competition is not consistent with these arguments. Trade competition is likely endogenous. This is problematic for the identification of the coefficient of the environmental effort only if environmental effort causes change in trade competition. It is unlikely since trade competition is an aggregate at the industry level while environmental effort is defined at the firm level.[35]

Column 3 and 4 of table 4.2 presents the OLS estimation results for the effect of environmental effort on the direction of innovation. Column 3 does not contain a lag of the environmental effort variable while column 4 does. For current environmental effort in column 3, I find a coefficient equal to 0.1026 and statistically significant from zero at the 1% level. In column 4, I find that only the coefficient of the lag environmental effort variable

[35] Individual effort at the firm level causes change in trade competition at the industry level only if two conditions are met. First, environmental effort decreases firm productivity. The result of last section suggests that it does not. Second, the industry is extremely concentrated so that the effort of one firm have a sizeable impact on the industry aggregate. In most industries, this second condition is not fulfilled.

is significantly different from 0. The estimate of this coefficient is 0.1428. The two results indicate that a higher environmental effort leads to a higher share of green innovation. The estimation of column 4 suggests that the change in the direction of innovation is not immediate but takes time.

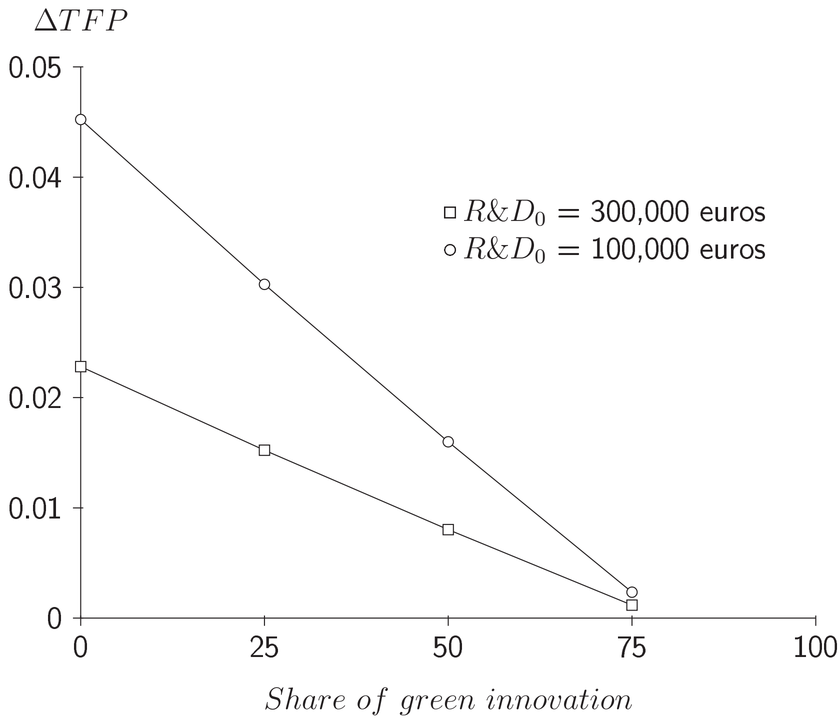
A conclusion emerges from the estimations reported in table 4.2. Higher environmental effort does not lead to a change in the scale of innovation but it alters the direction of innovation towards greener technologies. While the former result is new, the latter result is consistent with what is found in the literature. In the more reliable specification, I find that increasing environmental effort by 10 percentage points leads to an increase in the share of green innovation by 1 percentage point. The size of this effect is coherent with the theory that firms react to environmental regulations more by investing in green technology provided by firms specialized in the production of these technologies rather than developing their own green technologies. However, it is important to note that this paper does not test this theory.

4.5.3 Green innovation and productivity

Column 1 of table 4.3 show the OLS estimation results of equation (4.7). The coefficient of R&D expenditure equals 0.0111 and is statistically different from zero at the 1% level. This coefficient can almost be interpreted as an elasticity. Therefore, the initial amount of R&D expenditure influences importantly the return of productivity. The lower the initial amount, the higher the productivity return. Also, the marginal productivity return is decreasing in the amount of additional R&D. The coefficient of the share of green innovation is not statistically significant. However, the coefficient of the interaction between R&D expenditure and the share of green innovation equals -0.0002 and is statistically significant from zero at the 5% level.

To give more economic meaning to these coefficients I compute the marginal effect for an increase in 300,000 euros in R&D expenditure for different shares of green innovation for a median firm. Results are plotted in figure 4-2. The circle points correspond to the marginal effect of additional R&D expenditure when the firm's initial amount of expenditure is 100,000 euros. The square points correspond to an initial amount of 300,000 euros, the median amount of R&D expenditure for the firms in our sample. An increase in R&D expenditure from 100,000 euros to 400,000 euros is predicted to increase total factor productivity by 0.030 points if the share of green innovation is 25% and by 0.016 points if the share of green innovation is 50%.[36] The distribution mode of TFP is 2.6 in our estimation sample. In other words, this increases in R&D expenditure is predicted to increase the amount of output produced with the same amount of inputs by 1.2% if the share of green innovation is 25% and by 0.6% if the share of green innovation is 50%. This illustrates that innovating in green technologies can slow in a sizeable manner raise in productivity due to investment in R&D.

Figure 4-2: Productivity return on 300,000 euros of R&D expenditure



Column 2 of table 4.3 show the TSLS estimation results of equation (4.7) where I include environmental effort as an additional regressor. This allows me to test whether environmental effort has an impact on productivity that is not mediated by innovation as pictured by arrow

[36] An increase from 300,000 euros to 600,000 euros is predicted to increase total factor productivity by 0.015 points if the share of green innovation is 25% and by 0.008 points if the share of green innovation is 50%.

(f) in figure 4-1. The null hypothesis that the coefficient of environmental effort equals zero is not rejected by the data. The test for under-identification indicates that our instrumental variable is strong.

4.5.4 Compliance operating costs and firm profitability

Estimation results of equation (4.8) are presented in table 4.4. The coefficient of the share of environmental expenditure equals -0.288 and is found to be statistically different from zero at the 1% level. The control variables have the expected signs. I find that a 10% increase in the share of environmental expenditure is predicted to decrease operating margin by 0.03 percentage points. To provide economic meaning to this result, I also calculate marginal effects. At the sample mean, if the share of environmental expenditure increases from the mean (0.6%) by one standard deviation (1%), the operating margin is expected to decrease by 0.3 percentage points. A more important increase from the mean by 10% is expected to decrease operating margin by 0.8 percentage points. The effect of environmental regulations is rather small considering that the median margin is equal to 6.3 %.

Table 4.1: Environmental effort and productivity

	Dependent variable: Log (TFP)			
	TSLS	OLS		
	(1)	(2)	(3)	(4)
Environmental effort (%)	0.0024	-0.0000	-0.0001	-0.0001
	(0.0043)	(0.0001)	(0.0001)	(0.0001)
Environmental effort (%) t - 1			0.0000	0.0000
			(0.0001)	(0.0001)
Economic performance t - 1				0.2709***
				(0.0225)
Financial independence	0.0213***	0.0205***	0.0277***	0.0201***
	(0.0036)	(0.0030)	(0.0042)	(0.0038)
Age	0.0004	0.0003	0.0010	0.0007
	(0.0007)	(0.0005)	(0.0008)	(0.0006)
Trade competition (%)	-0.0003	0.0015	0.0075	0.0057
	(0.0028)	(0.0027)	(0.0052)	(0.0039)
Industry concentration	0.0309	-0.0073	-0.0430	-0.0343
	(0.0825)	(0.0687)	(0.0903)	(0.0743)
Year dummies	Yes	Yes	Yes	Yes
Industry × year dummies	No	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	5.13**			
Number of observations	43,018	54,402	30,056	29,764
Number of firms	8,417	15,719	8,115	8,074
Average number of observations per firm	5.1	3.5	3.7	3.7

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.2: Environmental effort, scale and direction of the innovation

	Dependent variable			
	R&D expenditure		Green innovation (%)	
	PPML		OLS	
	(1)	(2)	(3)	(4)
Environmental effort (%)	-0.0054	-0.0119	0.1026***	0.0299
	(0.0089)	(0.0089)	(0.0268)	(0.0554)
Environmental effort (%) t - 1		-0.0099		0.1428***
		(0.0117)		(0.0520)
Log (number of employees)	1.317***	1.2456***	1.9604***	2.0502***
	(0.0665)	(0.0605)	(0.2123)	(0.3448)
Financial independance	0.0181	-0.0185	0.2039	0.2659
	(0.0417)	(0.0696)	(0.2163)	(0.3260)
Trade competition (%)	-0.1899**	0.2432***	-0.5396	-1.2418
	(0.0757)	(0.0734)	(0.4381)	(1.6288)
Industry concentration	-6.7867***	-30.2825***	46.8136**	116.3262
	(2.1883)	(6.9643)	(23.2745)	(154.4940)
Age	-0.0121***	-0.0067*	-0.0045	0.0060
	(0.0043)	(0.0034)	(0.0139)	(0.0216)
Industry-period dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No
Number of observations	5,182	1,921	4,538	1,883
Number of firms	3,163	1,220	2,717	1,200
Average number of observations per firm	1.6	1.6	1.7	1.6

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.3: Green innovation and productivity

	Dependent variable	
	TFP	
	OLS	TSLS
	(1)	(2)
R&D expenditure	0.0111***	0.0187***
	(0.0021)	(0.0052)
Green innovation (%)	0.0004	0.0015
	0.0004)	(0.0011)
R&D expenditure × Green innovation (%)	-0.0002**	-0.0003*
	(0.0001)	(0.0002)
Environmental effort (%)		-0.0017
		(0.0095)
Financial independance	0.0152***	0.0281***
	(0.0056)	(0.0107)
Age	-0.0004	0.0008*
	(0.0003)	(0.0004)
Trade competition (%)	0.0045	-0.0038
	(0.0128)	(0.0027)
Industry concentration	0.4629	-0.0003*
	(0.5149)	(0.0002)
Industry-period dummies	Yes	Yes
Firm fixed effects	No	No
Kleibergen-Paap rk LM statistic		8.58***
Number of observations	11,049	4,216
Number of firms	7,573	2,548
Average number of observations per firm	1.5	1.7

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
R&D expenditure is transformed with the inverse hyperbolic sinus function
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 4.4: Compliance operating costs and profitability

	Dependent variable: Operating margin
	OLS
Log (Share of environmental expenditure)	-0.288***
	(0.090)
Operating margin t - 1	0.730***
	(0.054)
Log (TFP)	3.095***
	(0.424)
Log (Market share)	0.320***
	(0.073)
Financial independance	0.285*
	(0.148)
Log (Average wage)	-1.856***
	(0.502)
Firm fixed effects	No
Industry × year dummies	Yes
Number of observations	5,653
Number of firms	4,762
Average number of observations per firm	1.2

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
Two digits NACE 2 industry dummies
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

4.6 Robustness Checks

4.6.1 Environmental effort and productivity

Firm-level aggregation of plant-level data

In section 4.4.2, I explain that firms having no plant appearing in Antipol are dropped from the estimation sample. In addition, I assume that the pollution abatement capital expenditures of plants absent from the Antipol survey are equal to zero or very small in comparison to reporting plants. If a firms have numerous small plants that are not surveyed by Antipol and one big plant surveyed by Antipol, one concludes under the previous assumption that the firms total pollution abatement capital expenditure equal the firm's big plant expenditure. However, if the sum of the small plants' expenditures is not small compared to the big plant expenditure, then the firms' expenditure is underestimated. This measurement error could bias the coefficient of interest.

A solution consists in restricting the sample to a certain group of firms. One can include firms in the sample according to the ratio between firm's total number of employees for plants where pollution abatement capital expenditure data are available and firm's total number of employees. Firms having this ratio below a given % threshold are not included in the sample. A ratio equal to 100% ensures that there is no measurement error due to the aggregation but restricts the sample considerably.

In table 36, I run the base estimation of equation (4.1) when logged TFP is the dependent variable using different thresholds. Column 1 reports the estimation with the base sample, column 2 corresponds to a threshold of 50%, column 3 corresponds to a threshold of 75%, and column 4 corresponds to a threshold of 90%.[37] The 3 thresholds leads to the selection of 10,000 firms. Therefore, these 3 strategies are quite similar. For column 2, 3, and 4 I find a point estimate of 0.0002. This is slightly different from the zero estimate I find in

[37] Note that I do not use TSLS estimator because the threshold methodology makes the instrumental variable available only for a tiny share of firms. As a result, the instrument is not strong since the null hypothesis that the model is under-identified cannot be rejected.

the base estimation. This changes can result from 2 factors. First, the measurement error of the environmental effort variable could be lower when using a non null threshold. If the measurement error generates endogeneity, then the estimate is less biased. Second, the composition of the sample changes. Only a certain category of firms appear in the sample. The selection may be endogenous and generate a bias in the estimate.[38] It is not possible to know which of these 2 factors provoke the change in the point estimate.

Looking at the standard errors, I find that the coefficient is significantly different from zero at the 10% level for the 50% threshold and at 5% level for the 90% threshold. However, it is not significant for the 75% threshold. This non monotonicity in the student test outcomes suggests that increasing the threshold may not be helping identification and that the sample composition effect is responsible for the difference between the base estimate and the threshold estimates. If one assumes that the threshold methodology actually lower the bias in the estimate, one concludes that the effect is very small. If there is a substantial increase in environmental effort by 10 percentage points, TFP is predicted to increase by only 0.2% other things equal. I conclude that the main results are not highly sensitive to the aggregation methodology from plant data to firm data.

TFP measurement

When computing the base measure of TFP I make several methodological choices. First, I do not include energy in the list of outputs because it limits significantly the number of observations and could bias the estimations since only big firms are asked to provide their energy consumption in the EACEI. Second, I proxy the quantity of labour used with total working hours while some studies use wages.[39] Third, I use nominal turnover instead of real turnover. Although it would be more appropriate, using real turnover reduces the number of observations by 60%. I compute 7 additional measure of TFP by combining these

[38] For instance, I may select mostly pollution intensive firms because even their smallest plants have to answer to the Antipol survey while cleaner plants do not.
[39] If one assumes that wage equals labour productivity, then total wages is an accurate measure of the total quantity of labour used. But this assumption can fail (Syverson, 2011).

methodological choices. Table 37 in the appendix shows the correlation coefficients between these 8 different measures of TFP for year 2006. The estimated coefficients vary from 0.89 to 0.99 and are significant at the 1% level. This result holds for the other years of observations and implies that these measures capture the same thing. When running the estimations with these different measures, I get highly similar coefficients.[40]

Functional form

I perform a regression specification error test (RESET) to test whether equation (4.1) has a general functional form misspecification. More specifically, I perform two tests. First, I test whether the coefficient of the square value of the predicted value of the dependent variable is statistically different from zero when I include it as an additional control in equation (4.1). I find a heteroskedasticity-robust LM statistic equal to 1.047 and a p-value equal to 0.592. Second, I test whether the coefficients of the square and the cube value of the predicted value of the dependent variable are jointly different from zero when I include them as additional regressors in equation (4.1). I find a heteroskedasticity-robust LM statistic equal to 3.266 and a p-value equal to 0.195. Both tests indicate that we cannot reject general functional form misspecification.

Environmental effort enters equation 4.1 in level. The true functional form is unknown and perhaps it is different. To check whether the main results are sensitive to functional form specification, I run estimations of equation 4.1 where the environmental effort variable is logged. Column 2 of table 39 in the appendix contains the estimation results when the dependent variable is logged TFP. Column 1 replicates the base estimation on the same sample as column 2 that is when the environmental effort is higher than 0. Whether in level or logged, I find that the null hypothesis that environmental effort has no effect on TFP is not rejected.

Potential outlying observations

[40]Tables available upon request.

I now verify if potentially influential observations drive the main results. Results are displayed in table 40. In column 1 I estimate equation (4.1) with TSLS but I drop firms that are above the 90% percentile of the environmental effort distribution that is firms with an environmental effort lower than 17.4%. I find an estimate of 0.0053 but it is not statistically different from zero. The instrument is strong since the Kleibergen-Paap LM statistics is significantly different from 0 at the 1% level. In column 2 I estimate equation (4.1) with TSLS but I drop firms that are below the 10% and above the 90% percentile of the logged TFP distribution so that I drop firms with a logged TFP below 0.4 and a logged TFP above 1.6. I find an estimate of 0.0066 but I cannot reject the null hypothesis that the coefficient equals zero. The instrument is relatively strong since the Kleibergen-Paap LM statistics is significantly different from 0 at the 5% level.

Controlling for geographical externalities

The baseline identification strategy does not control for agglomeration effects and other positive externalities. For instance, environmental regulations may affect a firm TFP differently depending on the area the firm operates. A firm located in a dynamic industry cluster and a more isolated firm may not respond to regulations the same way. To control for such agglomeration effects, I estimate equation (4.1) by adding region times year dummy variables. Results are reported in table 41 of the appendix. As in the baseline estimation, I fail to reject the null hypothesis that environmental regulations has no effect on total factor productivity.

Sector heterogeneity

The baseline empirical strategy aims to estimate an average effect across all sectors of the French economy. However, this average estimate that is close to zero could result from heterogeneity across sectors. Economics sector differ greatly in pollution intensity as well as in capital intensity. Firms may not be affected by environmental regulations the same way depending on their economic activity. For example, the manufacture of computer, electronic and optical products is not highly pollution intensive and may not be affected significantly by environmental regulations whether they have a positive or a negative impact on productivity. In contrast, the manufacture of pulp, paper and paper products is much more pollution intensive. If environmental regulations have an effect, it is likely of greater size for the manufacture of papers than for the manufacture of computers. To check whether the null average effect estimated in the baseline comes from sector heterogeneity, I estimate equation (4.1) for each 2 digits NACE sectors for which there are at least 1,000 observations.[41] Results are reported in table 42. For the large majority of the 35 manufacturing sectors, I fail to reject the null hypothesis. I find a positive and significant for only 2 sectors: Food products and Pharmaceutical products. However, the size of the coefficient is not economically significant. These estimation results suggest that the baseline results does not come from sector heterogenity.[42]

4.6.2 Environmental effort, scale and direction of innovation

Endogenous environmental effort

I assumed that the environmental effort is exogenous in equation (4.4) and in equation (4.5). It is possible that this assumption does not hold. To tackle this issue, I use the control function poisson estimator to estimate equation (4.4) and the TSLS estimator to estimate equation (4.5) using $SIMENV$ as instrumental variable. The results are presented in Table 44. Column 1 contains the estimated coefficient for the control function approach. We find a negative although not significant coefficient for the effect of environmental effort on the scale of innovation. The first-stage coefficient of the instrumental variable seems to indicate that the instrument is strong. The conclusion is the same as the base estimation. Column 2 contains the estimated coefficient for the TSLS approach. I find a coefficient of 0.1048 that is similar to our base estimation. The instrument is strong since the Kleibergen-Paap

[41] The 1,000 observations threshold is to ensure that the firms of the estimation sample represent the actual population.

[42] Applying the first difference estimator gives similar although not identical results. In any case, the coefficients found are economically small.

LM statistics is significantly different from 0 at the 1% level. This indicates that our base estimation with the OLS estimator is not biased. An increase of 10% in the environmental effort is associated with an increase of 1% in the share of green innovation.

Placebo test

To check whether the effect found in table 4.2 is specific to the share of green innovation, I estimate equation (4.4) using the share of other innovations as dependent variables. Table 45 of the appendix presents the results of these estimations. In column 1, the dependent variable is the share of innovations aiming to increase the range of goods or services of the firm. In column 2, it is the share of innovations aiming to enter new markets or to increase the market share of the firm. In column 3, it is the share of innovations aiming to improve the quality of goods or services provided by the firm. In column 4, it is the share of innovations aiming to improve the flexibility of the production process. In column 5, it is the share of innovations aiming to reduce labour cost per unit of output. On the five coefficients estimated, the coefficient of quality, flexibility, and labour saving are not statistically different from zero. The coefficients of product range and new market are negative and statistically different from zero. This result is still consistent with our base estimation result. If the raise of environmental effort leads to a higher share of green innovation. It is expected that the share of other kinds of innovation diminishes as environmental effort increases.

4.6.3 Green innovation and productivity

Functional form

I perform a RESET to test whether equation (4.7) has a general functional form misspecification. More specifically, I perform two tests. First, I test whether the coefficient of the square value of the predicted value of the dependent variable is statistically different from zero when I include it as an additional control in equation (4.7). I find a heteroskedasticity-robust LM statistic equal to 0.280 and a p-value equal to 0.869. Second, I test whether the coefficients of the square and the cube value of the predicted value of the dependent variable are jointly different from zero when I include them as additional regressors in equation (4.7). I find a heteroskedasticity-robust LM statistic equal to 2.683 and a p-value equal to 0.261. Both tests indicate that we cannot reject general functional form misspecification.

In column 1 of table 46, I estimate equation (4.7) without the interaction term. I find a positive coefficient that is statistically different from zero at the 1% level for the R&D expenditure variable. The coefficient is slightly lower than the base estimate. I find a coefficient equal to -0.0004 that is significant at the 10% level. These coefficients indicates that for a given value of R&D expenditure, an increase of 10% in the share of green innovation is predicted to decrease TFP by 0.4%. This result is consistent with the base result that the share of green innovation has a negative effect on productivity for most value of R&D expenditure. In column 2 and 3 of table 46, the R&D expenditure variable is transformed using the natural log function. Both estimation results show that increasing the share of green innovation has a negative effect on productivity. In column 3, I find a coefficient for the interaction term equal to -0.0003 that is slightly bigger than the estimate of the base estimation. I find the same coefficient when I run the base estimation of column 1 of table 4.3 on the restricted sample. The difference in the coefficient is due to the modification of the sample and not to the transformation of the R&D variable.

4.6.4 Compliance operating costs and firm profitability

Additional control and different estimator

One could argue that it is necessary to control for firm general tax weight in equation (4.8). This is because the stringency of other tax policies that affects firm profit may be correlated positively with environmental policy stringency. Column 2 of table 47 provides the OLS estimates when I add the share of tax expenditure measured by the ratio between total taxes paid and turnover as an additional control variable. Column 1 reports the base estimation results for comparison. With the additional control, the coefficient size is halved but is still statistically significant from zero. The lower size may be due to the fact that the share of tax expenditure already captures environmental taxes. In column 3 and 4, I use an alternative estimator. I compute the difference between 2010 and 2004 for each variable and then run an OLS estimation. Column 3 excludes the general tax policy control included in column 4. For both estimations, a negative coefficient statistically different from zero is found. It is not directly comparable to previous estimates since the sample is different but it supports the previous result that compliance operating costs reduce firm profitability.

Functional form

I perform a RESET to test whether equation (4.8) has a general functional form misspecification. More specifically, I test whether the coefficient of the square value of the predicted value of the dependent variable is statistically different from zero when I include it as an additional control in equation (4.8). I find a heteroskedasticity-robust LM statistic equal to 2.158 and a p-value equal to 0.340. The test indicates that we cannot reject general functional form misspecification. Furthermore, to check whether the main results are not specific to the functional form of equation (4.8), I estimate an equation with the same regressors without any log transformation. Results are reported in table 48 of the appendix. I find a coefficient equal to -34 for the share of environmental expenditure. The student test rejects the null hypothesis at the 10% level. An increase of 1% in the share of environmental expenditure is predicted to increase operating margin by 0.3 percentage points. This is what I find when calculating the marginal effects in the base estimation.

4.7 Conclusion

In this paper, I combine firm-level financial data with information on pollution abatement capital investment, pollution abatement operating costs and innovation activities to examine the impact of environmental regulations on profitability. Using a pooled data set of 8 thousand French manufacturing firms, I find robust evidence that higher environmental effort leads to a change in the direction of innovation towards cleaner technologies but has no effect on the scale of innovation. I also find that the productivity return on R&D expenditure is lower as the share of green innovation increases. An increase in R&D expenditure from 100,000 euros to 400,000 euros is predicted to increase total factor productivity by 0.030 points if the share of green innovation is 25% and by 0.016 points if the share of green innovation is 50%. Using a panel of 16 thousand French companies observed during fifteen years, I find robust evidence that firms investing more in pollution abatement capital are not more or less productive than firms invest less in pollution abatement capital. If environmental regulations is not found to influence firm productivity level, it is found to have a small negative impact on firm profitability. At the sample mean, an increase in the share of environmental expenditure in a firm's total operating expenditure by one standard deviation (a move from 0.6% to 1.6%) is predicted to decrease the firm's profitability by 0.3 percentage points.

This paper has important policy implications. The results suggest that the impact of environmental regulations is null or very small on firm technology level and rather small on firm profitability. Overall, environmental regulations may harm one dimension of competitiveness but their impacts should not be overestimated in policy evaluations. Recent empirical works suggest that green innovations driven by regulations spill over the whole economy and are beneficial to societies (Dechezleprêtre and Sato, 2014). This is important to take into account these different effects when evaluating environmental policies. The paper provides evidence against the Porter Hypothesis. As regulations do not appear to lead firms to be more productive, the negative impact of regulations on profitability cannot be offset. Although the paper provides support for one hypothesis of Porter and Van der Linde (1995) that is: environmental regulations lead to develop more green innovation, it provides evidence against their other hypothesis that is: environmental innovation leads to productivity gains.

This work could be extended in several directions. First, it would be interesting to estimate the impact of individual environmental regulations on the environmental effort to support the claim that the environmental effort is a convincing proxy for regulations. Second, the results on the role of innovation and on the impact of compliance environmental costs on profitability rely on a pooled data set. This makes controlling for unobserved heterogeneity difficult. Also, the data from the CIS are firm ”perceived” effects of their innovation. One way to improve that is to use patent data that are indicator of actual innovation. However, it is not yet possible to identify every green innovation in the current patent nomenclature. Being capable to identify technologies that improves material productivity in patent data is an important avenue for future research.

General conclusion

In the first chapter, I find that variation in domestic waste taxes can have significant impact on transboundary movements of wastes. The size of the impacts varies across countries that are different in size, geographical location, and initial waste management cost. I show that countries with low waste taxes attract waste from countries with higher taxes. Therefore, transboundary movements of waste within the EU is likely to result in higher aggregate pollution. This outcome is inefficient if the stringency of national waste regulations is set below the marginal damage of pollution.

Should the EU level the playing field in terms of waste regulations? In other therms, should all EU member states have the same waste regulations? Cross-country differences in preferences, infrastructure and endowment in natural resources may justify the existence of country specific environmental policy stringency. Setting a tax higher or lower than the marginal damage of pollution leads to welfare loss. The EU should encourage the introduction of efficient environmental regulations but also limit races to the bottom such as Norway and Sweden synchronized incineration tax removal.

Chapter 1 illustrates that countries can effectively influence waste trade flows if they engage in strategic behaviours. This result calls for the effective implementation of international environmental agreement such as the Ban Amendment to the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal. This amendment prohibits each developed country that ratifies the amendment to export hazardous wastes towards developing countries. The Ban amendment has not yet entered into force because of an insufficient number of ratifying countries. Some countries such as the EU member states already transposed the Ban Amendment into national legislation but they still face issues related to illegal trade in waste.

In Chapter 2, I find that the development of waste metal recovery has no significant effect on the import of virgin materials but that is has a significant and negative effect on the import of secondary raw materials. More specifically, a 100 million USD increase in waste recovery is predicted to diminish import of metallic raw materials by 56 million USD on average. This result illustrates how waste recycling policies can benefit to the balance of trade. Although, waste metal recovery has not yet been able to substitute metallic ores on which some countries are highly dependent.

Switching to more circular economies that is utilizing more secondary raw materials require to improve waste collection, sorting, and recovery process as well as secondary raw material utilization technologies. Such innovations are costly. The more general question is whether country recycling targets are well defined. Few studies provide an answer to that questions. Further Cost Benefit Analyses should account for the trade effect to evaluate waste recycling targets in a comprehensive manner.

In Chapter 3, I find robust evidence that importing materials from low-cost countries diminish firms' propensity to develop clean innovation. A move from 3% to 15% in the share of materials imported from low-cost countries decreases firms' propensity to introduce a material or energy saving innovation by 14 percentage points. Considering that the share of OECD imports supplied by non-OECD countries increased from 25% to 36% between 1995 and 2011, this result suggests that trade with low-cost countries had a significant impact on clean innovation in developed countries.

The global interpretation of Chapter 3's finding is limited by the question of how developing countries react to higher production induced by trade with developed countries. If developing countries stay on the path of dirty technologies, then trade prevents or delays the development of green technologies. This makes the switch from clean to dirty technologies more costly as time passes. However, if developing countries react by developing more green innovation, then trade could be neutral to the development of clean innovation at the world level.

Finally, Chapter 4 investigates the still highly debated Porter Hypothesis. I find that past and current environmental regulations have not a significant impact on the technological performance of the firms. Firms switch to greener technologies as the regulations get stricter. It is found that the productivity return of R&D expenditure decrease with the share of green innovation. Nevertheless, this adverse effect is only important at high share of environmental innovation. Conditional on firm productivity level, I find that compliance costs have a negative but relatively small effect on profitability.

While this analysis conducted in Chapter 4 suggests that the Porter Hypothesis does not hold, it provides some evidence that environmental regulations are not as destructive as it is sometimes advocated. The negative impact of regulations on profitability may influence firms decision to exit or to offshore their activity. Nonetheless, as illustrated in the pollution haven literature, many other factors such as foot-looseness, labour cost, infrastructure are decisive. It seems difficult to argue that environmental regulations stringency is the primary factor of French firms relocation.

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Appendix

Tables

Table 5: Landfill tax and incineration tax rates in several European countries

Country	Landfill tax rate in 2008	Landfill tax rate in 2010	Incineration tax rate in 2008	Incineration tax rate in 2010
Austria	8-87	8-87	7	7
Belgium	20 - 77.3	60 - 79.6	0 - 7.2	0 - 7.4
Bulgaria	0	0	0	0
Croatia	0	0	0	0
Cyprus	0	0	0	0
Czech Republic	0	0	0	0
Denmark	50	63	52	40 - 50
Estonia	8.5	12	0	0
Finland	30	30	0	0
France	8.2 - 39.4	10.4 - 60	0	2-7
Germany	0	0	0	0
Hungary	0	0	0	0
Ireland	30	50	0	0
Italy	10-25	10-25	0	0
Latvia	0.4 - 35.8	4.3 - 35.6	0	0
Lithuania	0	0	0	0
Luxembourg	0	0	0	0
Netherlands	16.8 - 107.5	16.8 - 107.5	0	0
Norway	34 - 59	37.4	13	0
Poland	18	25	0	0
Portugal	3	3.5	1	1.1
Romania	0	0	0	0
Slovak Republic	0	0	0	0
Slovenia	2.2 - 36.7	2.2 - 22	0	0
Spain	3-35	3-35	0 - 5.5	0 - 5.5
Sweden	43	48	10-50	0
United Kingdom	40.8	54.1	0	0

Data sources: CEWEP country reports on waste management 2010 and 2012 ; EEA ETC/SCP 2013 ; ETC/SCP working paper 1/2012

Table 6: List of unprocessed waste and secondary raw materials in the trade nomenclature

HS6 Code	Description	Category	In Kellenberg (2012)	HS6 Code	Description	Category	In Kellenberg (2012)
262110	Ash & residues from the incineration of municipal waste	Unprocessed waste	1	510330	Waste of coarse animal hair	Secondary Raw Material	1
262021	Leaded gasoline sludges & leaded anti-knock compound sludges	Unprocessed waste	0	520210	Yarn waste (incl. thread waste), of cotton	Secondary Raw Material	1
271091	Waste oils cont. polychlorinated biphenyls (PCBs)	Unprocessed waste	1	520299	Cotton waste other than yarn waste	Secondary Raw Material	1
271099	Waste oils other than those cont. polychlorinated biphenyls (PCBs)	Unprocessed waste	1	550510	Waste (incl. noils, yarn waste & garneted stock) of synth. fibers	Secondary Raw Material	1
300692	Waste pharmaceuticals	Unprocessed waste	1	550520	Waste (incl. noils, yarn waste & garneted stock) of art. fibers	Secondary Raw Material	1
382510	Municipal waste	Unprocessed waste	1	700100	Cullet & other waste & scrap of glass; glass in the mass	Secondary Raw Material	0
382520	Sewage sludge	Unprocessed waste	0	711210	Waste or scrap containing gold as sole precious metal	Secondary Raw Material	0
382530	Clinical waste	Unprocessed waste	1	711220	Waste/scrap containing platinum as sole precious metal	Secondary Raw Material	0
382541	Halogenated waste organic solvents	Unprocessed waste	1	711291	Waste & scrap of gold, incl. metal clad with gold	Secondary Raw Material	1
382549	Waste organic solvents other than halogenated waste organic solvents	Unprocessed waste	1	711292	Waste & scrap of platinum	Secondary Raw Material	1
382550	Wastes of metal pickling liquors, hydraulic fluids, brake fluids, etc.	Unprocessed waste	1	711299	Waste & scrap of precious metal/metal clad with precious metal	Secondary Raw Material	1
382561	Wastes from chem./allied industries, mainly cont. organic constituents	Unprocessed waste	1	720410	Waste & scrap of cast iron	Secondary Raw Material	1
382569	Wastes from chem./allied industries, n.e.s. in Ch.38	Unprocessed waste	1	720421	Waste & scrap of stainless steel	Secondary Raw Material	1
382590	Residual prods. of the chem./allied industries, n.e.s. in Ch.38	Unprocessed waste	1	720429	Waste & scrap of alloy steel other than stainless steel	Secondary Raw Material	1
854810	Waste & scrap of primary cells, primary batteries	Electronical waste	1	720430	Waste & scrap of tinned iron/steel	Secondary Raw Material	1
854890	Electrical parts of mach./app., n.e.s. in Ch.85	Electronical waste	0	720441	Ferrous turnings, shavings, chips, milling waste, sawdust, filings	Secondary Raw Material	1
251720	Macadam of slag/dross/sim. industrial waste	Secondary Raw Material	1	720449	Ferrous waste & scrap (excl. of 7204.10-7204.41)	Secondary Raw Material	1
261900	Slag, dross (excl. granulated slag), scalings & oth. waste from mfr.	Secondary Raw Material	1	720450	Ferrous waste & scrap	Secondary Raw Material	0
262060	Slag, ash & residues (excl. from the manufacture of iron/steel) containing arsenic/mercury/thallium/their mixtures, of a kind used for the extraction of arsenic/those metals /for the manufacture of their chemical compound	Secondary Raw Material	0	740400	Copper waste & scrap	Secondary Raw Material	1
262100	Slag and ash n.e.s., including seaweed ash (kelp)	Secondary Raw Material	0	750300	Nickel waste & scrap	Secondary Raw Material	1
262190	Scories & ashes, incl. varech ashes.	Secondary Raw Material	0	760200	Aluminum waste & scrap	Secondary Raw Material	1
391510	Waste, parings & scrap, of polymers of ethylene	Secondary Raw Material	1	780200	Lead waste & scrap	Secondary Raw Material	1
391520	Waste, parings & scrap, of polymers of styrene	Secondary Raw Material	1	790200	Zinc waste & scrap	Secondary Raw Material	1
391530	Waste, parings & scrap, of polymers of vinyl chloride	Secondary Raw Material	1	800200	Tin waste & scrap	Secondary Raw Material	1
391590	Waste, parings & scrap, of plastics n.e.s. in 39.15	Secondary Raw Material	1	810197	Tungsten (wolfram) waste & scrap	Secondary Raw Material	1

Table 7: List of unprocessed waste and secondary raw materials in the trade nomenclature

HS6 Code	Description	Category	In Kellenberg (2012)	HS6 Code	Description	Category	In Kellenberg (2012)
400400	Waste, parings & scrap, of rubber (excl. hard rubber)	Secondary Raw Material	1	810297	Molybdenum waste & scrap	Secondary Raw Material	1
411000	Parings and other waste of leather	Secondary Raw Material	0	810330	Tantalum waste & scrap	Secondary Raw Material	1
411520	Parings & oth. waste of leather/composition leather, not suit. for mfr.	Secondary Raw Material	1	810420	Magnesium waste & scrap	Secondary Raw Material	1
470710	Recovered (waste & scrap) unbleached Kraft paper/paperboard	Secondary Raw Material	1	810530	Cobalt waste & scrap	Secondary Raw Material	1
470720	Recovered (waste & scrap) paper/paperboard mainly of bleached chem.	Secondary Raw Material	1	810730	Cadmium waste & scrap	Secondary Raw Material	1
470730	Recovered (waste & scrap) paper/paperboard made mainly of mech. Pulp	Secondary Raw Material	1	810830	Titanium waste & scrap	Secondary Raw Material	1
470790	Recovered (waste & scrap) paper/paperboard (excl. of 4707.10-4707.30)	Secondary Raw Material	1	810930	Zirconium waste & scrap	Secondary Raw Material	1
500300	Silk waste (incl. cocoons unsuitable for reeling, yarn waste & garneted stock)	Secondary Raw Material	1	811020	Antimony waste & scrap	Secondary Raw Material	1
500310	Silk waste (incl. cocoons unsuit. for reeling, yarn waste & garnetted stock)	Secondary Raw Material	1	811213	Beryllium waste & scrap	Secondary Raw Material	1
500390	Silk waste (incl. cocoons unsuit. for reeling, yarn waste & garnetted stock)	Secondary Raw Material	1	811222	Chromium waste & scrap	Secondary Raw Material	1
510310	Noils of wool or of fine animal hair	Secondary Raw Material	0	811252	Thallium waste & scrap	Secondary Raw Material	0
510320	Waste of wool/of fine animal hair, incl. yarn waste	Secondary Raw Material	1				

Table 8: Waste management performance of EU Member States

Group H	Overall score	Group L	Overall score
Austria	39	Hungary	19
Netherlands	39	Ireland	19
Denmark	37	Czech Republic	18
Germany	36	Poland	18
Sweden	35	Estonia	17
Belgium	34	Slovak Republic	17
Luxembourg	33	Italy	15
United Kingdom	32	Latvia	14
Finland	31	Cyprus	11
France	31	Romania	9
Slovenia	25	Lithuania	9
Spain	21	Bulgaria	8
Portugal	21	Greece	3
Norway	n.a.	Croatia	n.a.

The scores come from BiPro (2012).

Table 9: Top sample exporters and importers of unprocessed wastes

#	Top exporters	Quantity exported	Sample share	Top importers	Quantity imported	Sample share
1	Netherlands	285	19.9%	Belgium	288	20.2%
2	Germany	195	13.6%	Germany	257	18.0%
3	Norway	174	12.1%	Norway	216	15.1%
4	Belgium	138	9.6%	Sweden	155	10.9%
5	Sweden	129	9.0%	United Kingdom	115	8.0%
6	Denmark	121	8.4%	Spain	110	7.7%
7	France	120	8.3%	Netherlands	96	6.7%
8	Italy	119	8.3%	Denmark	59	4.1%
9	Austria	38	2.7%	France	50	3.5%
10	United Kingdom	35	2.4%	Italy	17	1.2%
	Total top ten	1,353	94.5%	Total top ten	1,363	95.4%

The quantity are reported in kilotons and are average on 2008 and 2010.

Table 10: Classification of waste management activities

Nace Rev. 2 group or class	Activities
38.2 – Waste treatment and disposal	Operation of landfills for the disposal of non-hazardous waste Disposal of non-hazardous waste by combustion or incineration or other methods, with or without the resulting production of electricity or steam, compost, substitute fuels, biogas, ashes or other by-products for further use etc. Treatment of organic waste for disposal Operation of facilities for treatment of hazardous waste Treatment and disposal of toxic live or dead animals and other contaminated waste Incineration of hazardous waste Disposal of used goods such as refrigerators to eliminate harmful waste Treatment, disposal and storage of radioactive nuclear waste
38.31 – Dismantling of wrecks	Disposal of used goods such as refrigerators to eliminate harmful waste Dismantling of automobiles, ships, computers, televisions and other equipment to obtain re-sell usable parts
38.32 – Recovery of sorted materials	Mechanical crushing of metal waste from used cars, washing machines, bikes etc. Mechanical reduction of large iron pieces such as railway wagons Shredding of metal waste, end-of-life vehicles etc. Other methods of mechanical treatment as cutting, pressing to reduce the volume Reclaiming metals out of photographic waste, e.g. fixer solution or photographic films and paper Reclaiming of rubber such as used tyres to produce secondary raw material Sorting and pelleting of plastics to produce secondary raw material for tubes, flower pots, pallets and the like Processing (cleaning, melting, grinding) of plastic or rubber waste to granulates Crushing, cleaning and sorting of glass Crushing, cleaning and sorting of other waste such as demolition waste to obtain secondary raw material

NACE is the nomenclature of economic activities adopted by the European Union.

Table 11: Classifications of waste disposal and recovery operations adopted by Eurostat

Waste management operations in Eurostat	Waste management operations in the Directive 2008/98/EC	NACE Rev. 2 group or class
Incineration with Energy recovery	R 1 Use principally as a fuel or other means to generate energy	38.2
Recovery (excluding energy recovery)	R 2 Solvent reclamation/regeneration	n.a.
	R 3 Recycling/reclamation of organic substances which are not used as solvents (including composting and other biological transformation processes)	38.2
	R 4 Recycling/reclamation of metals and metal compounds	38.32
	R 5 Recycling/reclamation of other inorganic materials	38.32
	R 6 Regeneration of acids or bases	n.a.
	R 7 Recovery of components used for pollution abatement	n.a.
	R 8 Recovery of components from catalysts	n.a.
	R 9 Oil re-refining or other reuses of oil	n.a.
	R 10 Land treatment resulting in benefit to agriculture or ecological improvement	38.2
	R 11 Use of waste obtained from any of the operations numbered R 1 to R 10	n.a.
Disposal on land	D 1 Deposit into or on to land (e.g. landfill, etc.)	38.2
	D 3 Deep injection (e.g. injection of pumpable discards into wells, salt domes or naturally occurring repositories, etc.)	38.2
	D 4 Surface impoundment (e.g. placement of liquid or sludgy discards into pits, ponds or lagoons, etc.)	38.2
	D 5 Specially engineered landfill (e.g. placement into lined discrete cells which are capped and isolated from one another and the environment, etc.)	38.2
	D 12 Permanent storage (e.g. emplacement of containers in a mine, etc.)	38.2
Land treatment/release into water	D 2 Land treatment (e.g. biodegradation of liquid or sludgy discards in soils, etc.)	38.2
	D 6 Release into a water body except seas/oceans	38.2
	D 7 Release to seas/oceans including sea-bed insertion	38.2
Incineration without Energy recovery	D 10 Incineration on land	38.2

This classification comes from Directive 2008/98/EC.
We attribute a NACE cdoe for each eurostat operation according to their definition.

Table 12: Waste heterogeneity and measurement of unit waste management

	Chemical waste	Food waste	Total
Cost in country A	4000	1600	5600
Quantity in country A	10	40	50
Unit Cost in country A	400	40	112
Cost in country B	3000	600	3600
Quantity in country B	10	20	30
Unit Cost in country B	300	30	120

Table 13: Additional waste trade robustness regressions

	PPML			
	Dependent variable: total unprocessed waste trade flow from i to j			
Data source	UN Comtrade	UN Comtrade	UN Comtrade	Eurostat
Measurement method	Maximum	Maximum	Import only	Maximum
Electronic waste included	No	Yes	No	No
	(1)	(2)	(3)	(4)
Waste management cost	0.826**	0.658**	1.062**	0.905***
difference	-0.321	-0.281	-0.488	-0.234
Log (Exporter's GDP)	1.165	0.437	-3.197	1.354
	-5.568	-2.929	-6.806	-4.352
Log (Importer's GDP)	4.248	2.076	-1.734	1.546
	-6.364	-3.79	-10.17	-7.984
Log (Distance)	-2.666***	-2.552***	-1.792***	-2.008***
	-0.379	-0.309	-0.466	-0.383
Contiguity	-0.0889	0.0828	0.978**	0.0567
	-0.332	-0.309	-0.444	-0.487
Common official language	1.563***	1.049***	0.762	2.230***
	-0.485	-0.391	-0.473	-0.48
Colonial ties	0.438	-0.246	-0.703	2.721***
	-0.814	-0.423	-1.147	-0.446
Observations	1,219	1,226	1,219	1,119
Country pairs	658	662	658	606
Exporter and Importer FE	yes	Yes	yes	yes
Time dummies	yes	Yes	yes	yes
Log Likelihood	-1.41E+09	-1.62E+09	-5.85E+08	-1.09E+07
Pseudo R-squared	0.84	0.84	0.9	0.85

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include a constant not reported for clarity.
Waste management cost difference is the difference between logged unit disposal cost.

Table 14: Panel composition of the base estimation sample

Country	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Observations
Austria		X	X	X	X	X	X	X	X	X	X	X	X	X	X	14
China										X	X	X	X	X	X	6
Czech Republic			X	X	X	X	X	X								6
Finland		X	X	X	X	X	X	X	X	X	X	X	X	X	X	14
France			X	X	X	X	X	X	X	X	X	X	X	X	X	13
Germany		X	X	X												3
Hungary			X	X					X		X	X	X	X	X	8
India								X			X	X		X		4
Ireland				X	X	X	X	X		X	X	X		X	X	10
Italy	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	15
Japan	X	X			X	X	X	X	X	X	X	X	X	X		12
Korea, Rep.									X		X		X			3
Malaysia								X	X	X		X	X	X	X	7
Norway		X	X		X		X	X	X	X			X	X	X	10
Poland		X	X	X	X	X	X	X	X	X	X	X	X	X	X	14
Portugal			X			X	X	X	X	X		X	X	X	X	10
Slovakia									X		X	X	X	X		5
Spain	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	15
Sweden		X	X	X	X	X	X	X	X	X	X	X	X	X	X	14
Turkey										X		X	X	X	X	5
United Kingdom	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	15

Table 15: Metallic raw commodities by material and by harmonized system code

Material	6-digit HS code HS code	Raw material	Description
Aluminum	260600	virgin	Aluminum ores and concentrates.
Aluminum	760200	secondary	Aluminum waste & scrap
Antimony	261710	virgin	Antimony ores and concentrates
Antimony	811020	secondary	Antimony waste & scrap
Beryllium	811213	secondary	Beryllium waste & scrap
Cadmium	810730	secondary	Cadmium waste & scrap
Chromium	261000	virgin	Chromium ores and concentrates.
Chromium	811222	secondary	Chromium waste & scrap
Cobalt	260500	virgin	Cobalt ores and concentrates.
Cobalt	810530	secondary	Cobalt waste & scrap
Copper	260300	virgin	Copper ores and concentrates.
Copper	740200	virgin	Unrefined copper; copper anodes for electrolytic refining.
Copper	740400	secondary	Copper waste & scrap
Gold	711210	secondary	Waste or scrap containing gold as sole precious metal
Gold	711291	secondary	Waste & scrap of gold, incl. metal clad with gold
Iron & Steel	260111	virgin	Iron ores and concentrates, other than roasted iron pyrites :– Non-agglomerated
Iron & Steel	260112	virgin	Iron ores and concentrates, other than roasted iron pyrites :– Agglomerated
Iron & Steel	720410	secondary	Waste & scrap of cast iron
Iron & Steel	720421	secondary	Waste & scrap of stainless steel
Iron & Steel	720429	secondary	Waste & scrap of alloy steel other than stainless steel
Iron & Steel	720430	secondary	Waste & scrap of tinned iron/steel
Iron & Steel	720441	secondary	Ferrous turnings, shavings, chips, milling waste, sawdust, filings
Iron & Steel	720449	secondary	Ferrous waste & scrap (excl. of 7204.10-7204.41)
Iron & Steel	720450	secondary	Ferrous waste & scrap
Lead	260700	virgin	Lead ores and concentrates.
Lead	780200	secondary	Lead waste & scrap
Magnesium	251910	virgin	Natural magnesium carbonate (magnesite)
Magnesium	810420	secondary	Magnesium waste & scrap
Molybdenum	261390	virgin	Molybdenum ores and concentrates (excl. Roasted)
Molybdenum	810297	secondary	Molybdenum waste & scrap
Nickel	260400	virgin	Nickel ores and concentrates.
Nickel	750300	secondary	Nickel waste & scrap

Table 16: Metallic raw commodities by material and by harmonized system code

Material	6-digit HS code HS code	Raw material	Description
Other non-ferrous metals	260200	virgin	Manganese ores and concentrates
Other non-ferrous metals	261590	virgin	Niobium, tantalum or vanadium ores and concentrates
Other non-ferrous metals	261790	virgin	Ores and concentrates (excl. iron, manganese, copper, nickel, cobalt, aluminum, lead, zinc, tin, chromium, tungsten, uranium, thorium, molybdenum, titanium, niobium, tantalum, vanadium, zirconium, precious metal or antimony ores and concentrates)
Other non-ferrous metals	280519	virgin	Alkali or alkaline-earth metals (excl. Sodium and calcium)
Other non-ferrous metals	280530	virgin	Rare-earth metals, scandium and yttrium, whether or not intermixed or inter-alloyed
Other precious	261690	virgin	Precious metal ores and concentrates (excl. Silver ores and concentrates)
Other precious	711290	secondary	Waste & scrap of precious metal or of metal clad
Platinum	711220	secondary	Waste/scrap containing platinum as sole precious metal
Platinum	711292	secondary	Waste & scrap of platinum
Precious metal	711299	secondary	Waste & scrap of precious metal/metal clad with precious metal
Silver	261610	virgin	Silver ores and concentrates
Tantalum	810330	secondary	Tantalum waste & scrap
Thallium	811252	secondary	Thallium waste & scrap
Tin	260900	virgin	Tin ores and concentrates.
Tin	800200	secondary	Tin waste & scrap
Titanium	261400	virgin	Titanium ores and concentrates.
Titanium	810830	secondary	Titanium waste & scrap
Tungsten	261100	virgin	Tungsten ores and concentrates.
Tungsten	810197	secondary	Tungsten (wolfram) waste & scrap
Zinc	260800	virgin	Zinc ores and concentrates.
Zinc	790200	secondary	Zinc waste & scrap
Zirconium	261510	virgin	Zirconium ores and concentrates
Zirconium	810930	secondary	Zirconium waste & scrap

Table 17: Price Index formulas

Index name	Formula
Geometric Paasche	$gP_{t/0} = \prod_k (\frac{p_{kt}}{p_{k0}})^{w_{kt}}$
Geometric Laspeyres	$gL_{t/0} = \prod_k (\frac{p_{kt}}{p_{k0}})^{w_{k0}}$
Arithmetic Paasche	$aP_{t/0} = (\sum_k w_{kt} \frac{p_{k0}}{p_{kt}})^{-1}$
Tornqvist	$Tornqvist_{t/0} = \sqrt{gP_{t/0}.gL_{t/0}}$

p_{kt} denotes the price of product k at year t.
w_{kt} denotes the share of product k in total sales at year t

Table 18: Import, recovery, mining, and demand for metallic raw materials by country

Country	Import of metallic raw materials	Metal recovery output	Metal mining output	Basic metal manufacturing output	GDP
Austria	866	170	28	9,650	331,429
China	15,787	3,173	18,267	293,833	7,866,667
Finland	971	281	96	6,309	194,286
France	1,406	2,730	14	30,186	2,271,429
Hungary	108	48	34	2,028	217,143
India	2,267	25	4,143	52,633	3,900,000
Ireland	141	100	307	418	192,000
Italy	2,250	1,821	141	43,329	2,085,714
Japan	8,057	12,058	137	135,667	4,300,000
Korea, Rep.	4,616	964	8	58,867	1,120,000
Malaysia	709	86	49	7,235	464,286
Norway	360	329	131	5,692	290,000
Poland	365	368	350	5,726	650,000
Portugal	126	108	54	2,588	270,000
Slovak Republic	165	21	27	1,974	105,167
Spain	2,679	1,366	182	22,843	1,414,286
Sweden	586	348	758	10,654	352,857
Turkey	2,301	110	203	15,880	1,021,429
United Kingdom	2,077	3,220	< 1	16,771	2,128,571
Median	971	329	130	10,654	650,000

Output and import are expressed in constant thousand USD and averaged over 2002-2008. Czech Republic and Germany do not appear in Table 2.1 and 2.2 because data are not available for this period of time.

Table 19: General Environmental Management technology fields

Code	Description
A.1.	Air Pollution Abatement
A.2.	Water Pollution Abatement
A.3.	Waste Management
A.3.1.	Solid Waste collection
A.3.2.	Material recovery, recycling and re-use
A.3.3.	Fertilizers from waste
A.3.4.	Incineration and energy recovery
A.3.5.	Landfilling
A.3.6.	Waste Management – Not Elsewhere Classified
A.4.	Soil Remediation
A.5.	Environmental Monitoring

Classification adopted by the OECD.

Table 20: First stage regression results

	First stage dependent variable					
	1		2		3	
	Log (recovery)	*Log (mining)*	*Log (recovery)*	*Log (mining)*	*Log (recovery)*	*Log (mining)*
Log (Population density)	9.916***	-0.230	9.661***	0.008	9.978***	-0.282
	(2.822)	(2.068)	(2.849)	(2.078)	(2.811)	(2.062)
Education	0.027***	0.028***	0.027***	0.028***	0.026***	0.028***
	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Log (Demand)	0.076	1.262***	0.051	1.275***	0.109	1.251***
	(0.184)	(0.439)	(0.181)	(0.441)	(0.189)	(0.439)
Log (GDP per capita)	-0.035	-0.535	0.026	-0.687	0.069	-0.53
	(0.722)	(0.868)	(0.728)	(0.917)	(0.728)	(0.874)
Tariff	0.118**	-0.056**	0.053***	-0.036**	0.304***	-0.119
	(0.051)	(0.027)	(-0.02)	(0.016)	(0.091)	(-0.08)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
F-test on excluded instrument	10.73***	5.19***	10.74***	5.03***	10.59***	5.24***
Observations	203	203	203	203	203	203

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All columns include a constant not reported for clarity.
Data on population density (people per sq. km of land area) come from the World Bank. Education is defined as the gross enrollment ratio in tertiary education, for which data come from the UNESCO Institute for Statistics.

Table 21: Harmonized System 2 digits codes for 'material' goods

Material subcategory	**HS code**	**Description**
minerals and mining	25	Salt, sulphur, earth, stone, plaster, lime and cement
minerals and mining	26	Ores, slag and ash
chemicals	28	Inorganic chemicals, precious metal compound, isotopes
chemicals	29	Organic chemicals
plastics	39	Plastics and articles thereof
forest products	44	Wood and articles of wood, wood charcoal
paper	47	Pulp of wood, fibrous cellulosic material, waste etc
paper include packaging products	48	Paper & paperboard, articles of pulp, paper and board
construction materials	68	Stone, plaster, cement, asbestos, mica, etc articles
glass	70	Glass and glassware
metals	72	Iron and steel
metals	73	Articles of iron or steel
metals	74	Copper and articles thereof
metals	75	Nickel and articles thereof
metals	76	Aluminium and articles thereof
metals	78	Lead and articles thereof
metals	79	Zinc and articles thereof
metals	80	Tin and articles thereof
metals	81	Other base metals, cermets, articles thereof

Table 22: Share of number of firms by NACE 2-digit industries

NACE Code	Description	Share of total number of firms
10	Manufacture of food products	<1%
11	Manufacture of beverages	0%
13	Manufacture of textiles	<1%
14	Manufacture of wearing apparel	<1%
15	Manufacture of leather and related products	<1%
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	<1%
17	Manufacture of pulp, paper and paper products	4%
18	Publishing, printing and reproduction of recorded media	2%
19	Manufacture of coke and refined petroleum products	1%
20	Manufacture of chemicals and chemical products	4%
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	4%
22	Manufacture of rubber and plastic products	4%
23	Manufacture of other non-metallic mineral products	1%
24	Manufacture of basic metals	9%
25	Manufacture of fabricated metal products, except machinery and equipment	11%
26	Manufacture of computer, electronic and optical products	5%
27	Manufacture of electrical equipment	3%
28	Manufacture of machinery and equipment n.e.c.	15%
29	Manufacture of motor vehicles, trailers and semi-trailers	10%
30	Manufacture of other transport equipment	<1%
31	Manufacture of furniture	4%
32	Other manufacturing	3%
33	Repair and installation of machinery and equipment	5%
35	Electricity, gas, steam and air conditioning supply	2%
36	Water collection, treatment and supply	4%
37	Sewerage	<1%
38	Waste collection, treatment and disposal activities; materials recovery	<1%
39	Remediation activities and other waste management services	<1%

NACE classification followed in this study is NACE Rev 2 - a European statistical classification system of economic activities corresponding to International Standard Industrial Classification of All Economic Activities (ISIC) Rev.4.

Table 23: Definition of the variables of Chapter 3

Variable	Description
New innovation (0/1)	A dummy that switches on to 1 when a firm reports having introduced either a product/service or a process innovation.
Environmental innovation	Reported score for the question "How important were innovations that reduce either use of energy or material per unit of output in your decision to innovate?" 0 - Not relevant, 1 - Low, 2 - Medium, 3 - High.
Environmental innovation (0/1)	1 if a firm answered low, medium, or high to the question above.
Share of 'material' imports from BRICS	Value of 'material' products from Brazil, Russia, India, China, and South Africa in total value of firm's 'material' imports per year.
Share of 'material' imports from Non-OECD	Value of 'material' products from Non-OECD region in total value of firm's 'dirty' imports per year.
Share of 'energy intensive' imports from low-wage countries	Value of 'energy intensive' products from countries which GDP per capita is lower than 5% of that of the U.S. in total value of firm's 'energy intensive' imports per year.
Exporter	Dummy variable equal to 1 if a firm exports in any given year and 0 otherwise.
Number of sourcing countries	Number of countries from which the firm imports any good.
Capital	Firm's book-value-based capital stock in thousand euros.
Size	Total number of employees.
Labour Productivity	Total turnover divided by the number of employees in thousand euros.
Innovation Spillover (%)	Number of other firms in the firm industry (4 digits NACE) that are located in the same French department and introduce a new innovation.
Competitiveness IV (%)	Instrumental variable equal to firm own import weighted by the product-level share of total U.S. imports from low-cost countries divided by the firm total own import (see section **??** for details).

Notes. Material products are intermediate goods that are not 'complex' e.g. primary plastic, crude steel, wood pulp, etcetera. Energy intensive goods consist in fuels and products from industries covered by the EU-ETS e.g. coal, crude steel, fertilizers, etcetera.

Table 24: Summary statistics for Chapter 3

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
New innovation (0/1)	10,355	0.87	0.34	0	1
Environmental innovation	10,355	1.36	1.15	0	3
Environmental innovation (0/1)	10,355	0.67	0.47	0	1
Share of 'material' imports from China & India in all 'material' imports (%)	10,355	2.97	12.85	0	100
Share of 'material' imports from low-wage countries in all 'material' imports (%)	10,355	3.14	12.93	0	100
Share of 'material' imports from BRICS in all 'material' imports (%)	10,355	4.01	14.51	0	100
Share of 'material' imports from non oecd countries in all 'material' imports (%)	10,355	10.63	22.96	0	100
Share of 'material' imports from EU countries in all 'material' imports (%)	10,355	63.75	35.79	0	100
Exporter (0/1)	10,355	0.93	0.25	0	1
Number of sourcing countries	10,355	8.65	5.65	0.50	52.50
$\ln(Capital)$	10,355	9.22	1.83	2.67	18.40
$\ln(Size)$	10,355	5.16	1.39	1.10	11.03
ln(Labor Productivity)	10,355	5.15	0.62	1.89	10.74
Innovation Spillover (%)	10,355	62.54	32.65	0	100
Inverse Mills Ratio	10,355	0.33	0.57	-2.37	1.99
Competitiveness IV (%)	10,355	4.41	5.68	0	89.37

Table 25: Definition of variables for Chapter 4

Variable	Description
Total factor productivity	Difference between logged output and the sum of logged inputs weighted by the input share in total production cost.
Operating margin (%)	Ratio between operating profit and turnover. Operating profit (or EBITDA) equals net earnings, before interest expenses, taxes, depreciation and amortization are subtracted.
Environmental effort (%)	End-of-pipe and integrated pollution control capital investment divided by total investment.
Share of environmental expenditure (%)	Total operating compliance costs divided by firm turnover.
Share of green innovation (%)	The size of the environmental effects divided by the sum of the size of all effects of the innovation developed by the firm.
Financial independence	Ratio between equity and total liabilities.
Trade competition (%)	Ratio between industry total import value and industry total domestic production.
Industry concentration (%)	Normalized Herfindahl-Hirschman Index.
Size	Number of employees.
Age	Number of years since the firm began to operate.
Average wage	Ratio between total wages paid to employees and the number of employees.
Market share (%)	Firm turnover divided by the turnover of its 3 digits NACE 2 industry.

Notes. EBITDA stands for Earnings Before Interest, Taxes, Depreciation, and Amortization

Table 26: Summary statistics of the panel data set used to estimate equation (4.1)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Log (Total Factor Productivity)	54,402	0.98	0.32	0.01	4.13
Environmental effort (%)	54,402	5.90	12.95	0	100
Financial independence	54,402	0.87	0.85	0	5.36
Age	54,402	24.90	16.17	1	111
Trade competition (%)	54,402	0.40	1.24	0	15.98
Industry concentration	54,402	0.04	0.06	0	1

Table 27: Summary statistics of the pooled data set used to estimate equation (4.4)

Variable	Obs.	Mean	Std. Dev.	Min	Max
R&D expenditure (thousand euros)	5,182	8,902	55,288	0	1,764,473
Environmental effort (%)	5,182	4.83	9.06	0	98.9
Financial independence	5,182	0.87	0.96	0	17.84
Age	5,182	24.11	14.84	1	52
Trade competition (%)	5,182	0.71	3.43	0	94.75
Industry concentration	5,182	0.05	0.07	0	0.54

Table 28: Summary statistics of the pooled data set used to estimate equation (4.5)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Share of green innovation (%)	4,538	21.89	12.77	0	100
Environmental effort (%)	4,538	4.71	8.93	0	98.9
Size	4,538	713	1,456	21	45,507
Financial independence	4,538	0.87	0.96	0	17.84
Age	4,538	24.22	14.91	1	52
Trade competition (%)	4,538	0.70	3.47	0	94.75
Industry concentration	4,538	0.05	0.07	0	0.54

Table 29: Summary statistics of the pooled data set used to estimate equation (4.7)

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Log (Total Factor Productivity)	11,049	0.99	0.32	0.01	3.25
Share of green innovation (%)	11,049	19.47	14.15	0	100
R&D expenditure (thousand euros)	11,049	5,303	39,509	0	1,764,473
Financial independence	11,049	0.84	0.96	0	17.84
Age	11,049	22.14	14.22	1	52
Trade competition (%)	11,049	0.60	3.34	0	94.75
Industry concentration	11,049	0.04	0.06	0	0.97

Table 30: Summary statistics of the pooled data set used to estimate equation (4.8)

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Operating Margin (%)	5,653	6.63	9.74	-198.42	91.23
Share of environmental expenditure (%)	5,653	0.61	1.04	0	21.05
Log (Total Factor Productivity)	5,653	0.96	0.32	0.05	3.05
Financial independence	5,653	0.89	0.86	0	5.33
Market share (%)	5,653	1.33	4.36	0	84.84
Average wage (thousand euros)	5,653	30.22	73.11	1.46	5,472

Figure -3: OLS fixed-effects year dummies point estimates for Log (TFP)

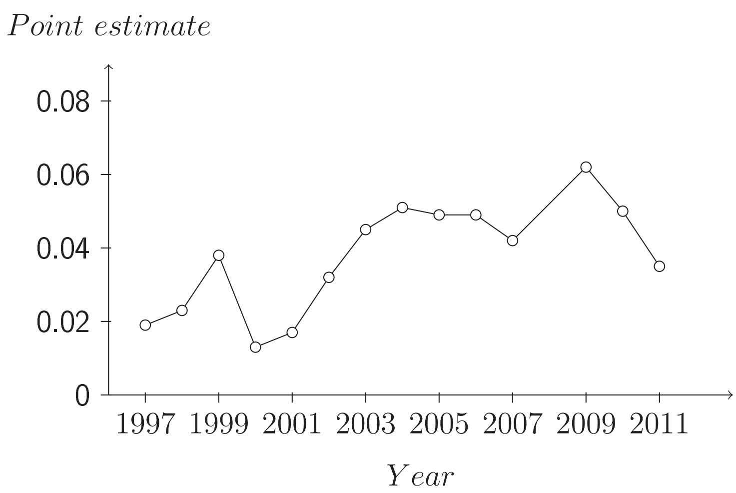


Figure -4: OLS fixed-effects year dummies point estimates for operating margin

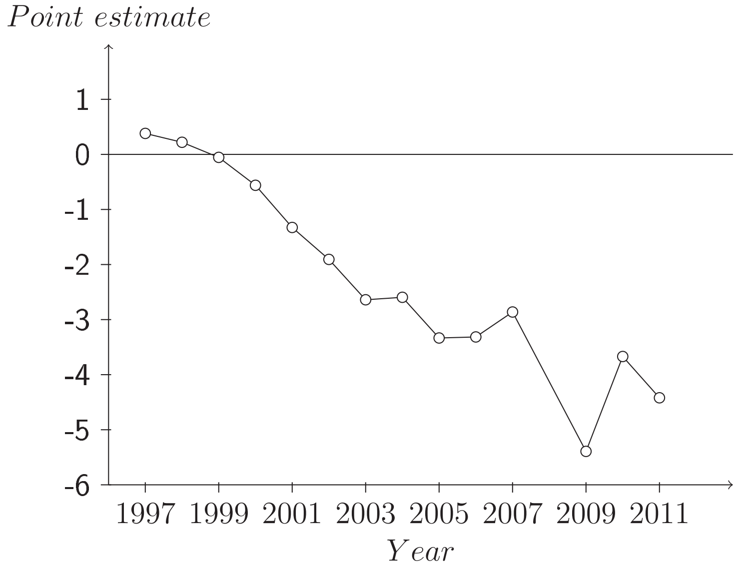


Figure -5: OLS fixed-effects year dummies point estimates for environmental effort

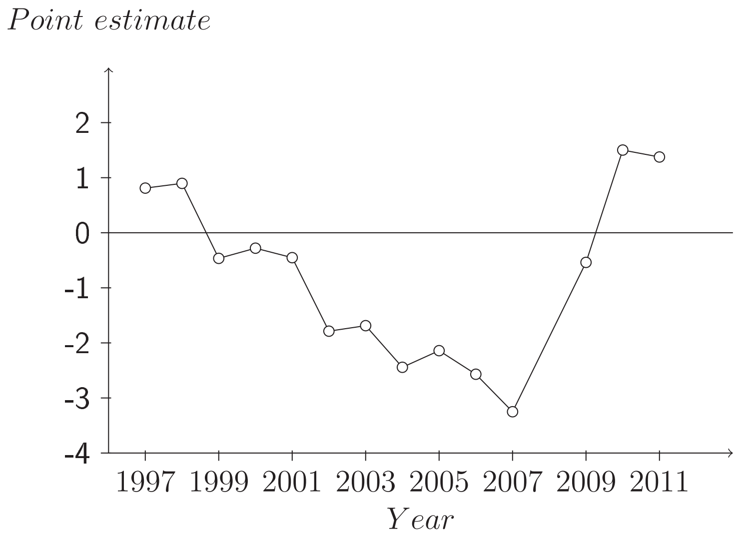


Table 31: Share of number of firms by NACE rev. 2 sectors

NACE code	Description	Panel data set	Pooled data set
10	Manufacture of food products	5%	<1%
11	Manufacture of beverages	1%	<1%
13	Manufacture of textiles	<1%	0%
14	Manufacture of wearing apparel	2%	1%
15	Manufacture of leather and related products	9%	15%
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	1%	<1%
17	Manufacture of pulp, paper and paper products	4%	4%
18	Publishing, printing and reproduction of recorded media	1%	2%
19	Manufacture of coke and refined petroleum products	1%	1%
20	Manufacture of chemicals and chemical products	4%	2%
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	4%	3%
22	Manufacture of rubber and plastic products	4%	4%
23	Manufacture of other non-metallic mineral products	2%	1%
24	Manufacture of basic metals	11%	10%
25	Manufacture of fabricated metal products, except machinery and equipment	11%	7%
26	Manufacture of computer, electronic and optical products	3%	5%
27	Manufacture of electrical equipment	4%	3%
28	Manufacture of machinery and equipment n.e.c.	11%	9%
29	Manufacture of motor vehicles, trailers and semi-trailers	7%	10%
30	Manufacture of other transport equipment	1%	1%
31	Manufacture of furniture	3%	5%
32	Other manufacturing	2%	3%
33	Repair and installation of machinery and equipment	3%	5%
35	Electricity, gas, steam and air conditioning supply	2%	2%
36	Water collection, treatment and supply	3%	4%
37	Sewerage	<1%	<1%
38	Waste collection, treatment and disposal activities; materials recovery	<1%	0%
39	Remediation activities and other waste management services	0%	0%

NACE classification followed in this study is NACE Rev. 2 - a European statistical classification system of economic activities corresponding to International Standard Industrial Classification of All Economic Activities (ISIC) Rev.4.

Table 32: Trend and cross-sector heterogeneity in TFP and profit

		Dependent variable			
		$\ln(TFP)$		*Operating margin*	
		Coef.	Std. Err.	Coef.	Std. Err.
Nace code	Trend	0.005***	(0.001)	-0.224***	(0.018)
11	Beverages	0.068*	(0.040)	5.802***	(1.214)
13	Textiles	0.170**	(0.020)	-1.936**	(0.878)
14	Wearing apparels	0.706***	(0.026)	8.651***	(0.652)
15	Leather	0.024**	(0.010)	-0.560**	(0.257)
16	Wood	0.129***	(0.016)	-1.925***	(0.624)
17	Paper	0.159***	(0.012)	-1.515***	(0.378)
18	Publishing and Printing	0.238***	(0.019)	-2.566***	(0.687)
19	Coke and refined petroleum products	0.040	(0.026)	-2.855***	(0.779)
20	Chemicals	0.161***	(0.013)	1.180***	(0.354)
21	Pharmaceutical products	0.201***	(0.014)	0.383	(0.421)
22	Rubber and plastic products	0.329***	(0.012)	-0.186	(0.315)
23	Other non-metallic products	0.306***	(0.031)	1.747***	(0.511)
24	Basic metals	0.235***	(0.013)	1.622***	(0.348)
25	Fabricated metal products	0.226***	(0.010)	-0.055	(0.267)
26	Electronics	0.295***	(0.015)	3.518***	(0.567)
27	Electrical equipment	0.201***	(0.014)	-0.979***	(0.371)
28	Machinery	0.300***	(0.010)	0.332	(0.260)
29	Motor vehicles	0.242***	(0.014)	-0.617*	(0.357)
30	Other transport	0.216***	(0.045)	-0.411	(0.755)
31	Furnitures	0.170***	(0.015)	-0.794	(0.486)
32	Other manufacturing	0.225***	(0.020)	-1.758**	(0.709)
33	Repair and installation of equipment	0.340***	(0.017)	-0.126	(0.685)
35	Electricity, gas, steam and air conditionning supply	0.433***	(0.035)	0.365	(0.636)
36	Water collection, treatment and supply	0.174***	(0.015)	-1.941***	(0.501)
37	Sewerage	0.312**	(0.132)	3.480*	(2.079)
38	Waste management	0.532*	(0.287)	-2.286	(5.762)
Number of observations		54,402		54,402	

All columns are estimated with OLS and include a constant (not reported)
The base group is the manufacture of food products.
Clustered standard errors robust to heteroskedasticity in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 33: Trend and cross-sector heterogeneity in environmental effort

		Dependent variable	
		Environmental effort (%)	
		Coef.	Std. Err.
Nace	Log (number of employees)	-0.598***	(0.063)
code	Trend	-0.196***	(0.022)
11	Beverages	0.343	(0.918)
13	Textiles	3.703***	(1.390)
14	Wearing apparels	0.637	(0.649)
15	Leather	-0.662*	(0.365)
16	Wood	0.809	(0.747)
17	Paper	-0.019	(0.480)
18	Publishing and Printing	-1.022	(0.651)
19	Coke and refined petroleum products	0.973	(1.013)
20	Chemicals	2.379***	(0.480)
21	Pharmaceutical products	0.998*	(0.516)
22	Rubber and plastic products	-0.456	(0.424)
23	Other non-metallic products	2.900***	(0.692)
24	Basic metals	2.100***	(0.405)
25	Fabricated metal products	-0.975***	(0.354)
26	Electronics	-0.139	(0.454)
27	Electrical equipment	2.567***	(0.534)
28	Machinery	-1.217***	(0.346)
29	Motor vehicles	-2.896***	(0.338)
30	Other transport	-0.481	(0.887)
31	Furnitures	-2.520***	(0.408)
32	Other manufacturing	-1.811***	(0.465)
33	Repair and installation of equipment	-3.879***	(0.0.375)
35	Electricity, gas, steam and air conditioning supply	-1.448***	(0.503)
36	Water collection, treatment and supply	-0.281	(0.532)
37	Sewerage	2.241	(1.776)
38	Waste management	-2.554	(1.976)
Number of observations		54,402	

All columns are estimated with OLS and include a constant (not reported)
The base group is the manufacture of food products.
Clustered standard errors robust to heteroskedasticity in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Figure -6: Distribution of the share of green innovation for 2002-2004

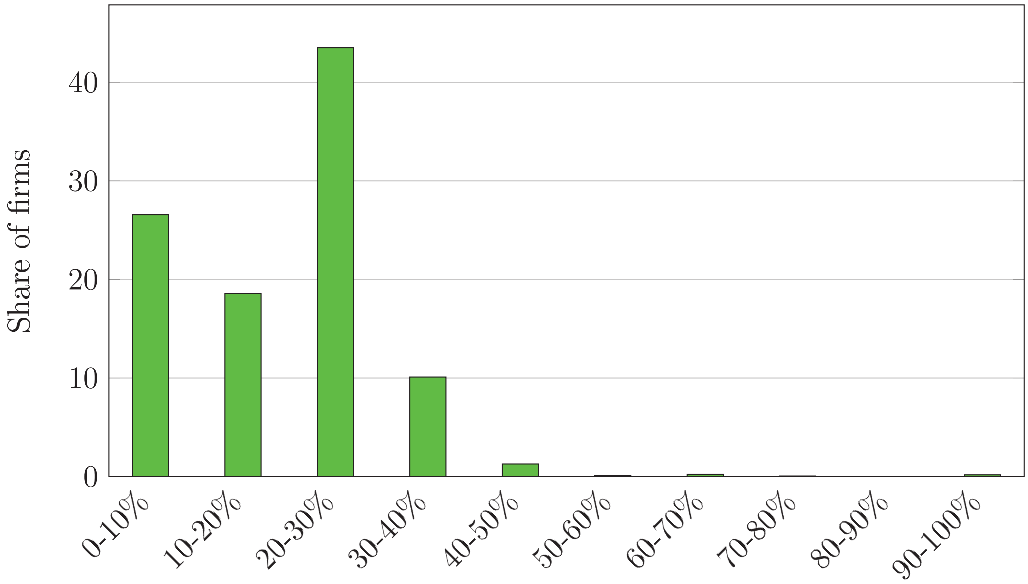


Figure -7: Distribution of the R&D expenditure for 2002-2004

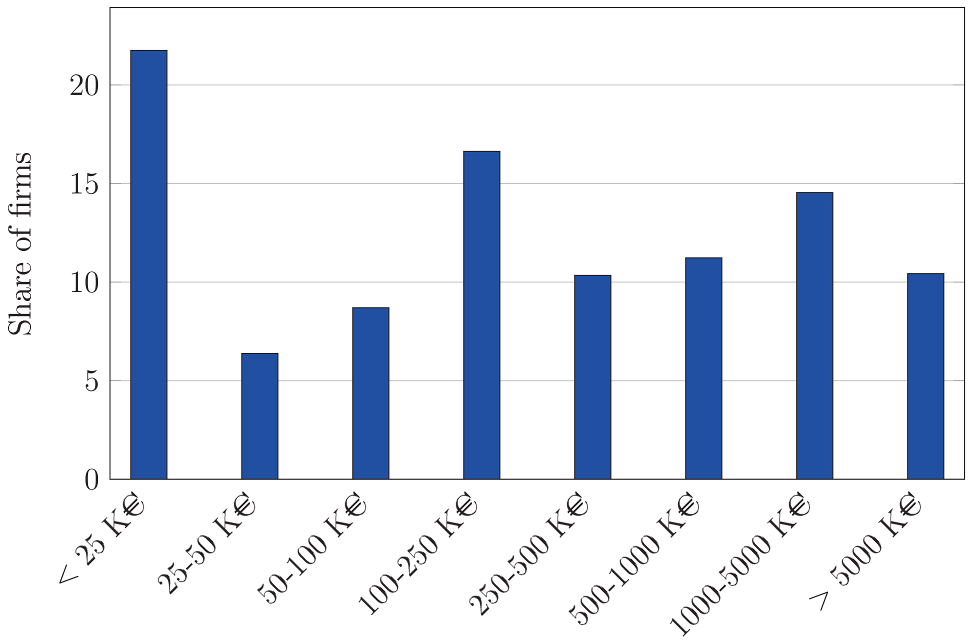


Table 34: Exposure to international competition by NACE 2-digit industries

NACE code	Description	Import divided by domestic production 1996-1998	2005-2007
10	Manufacture of food products	47%	66%
11	Manufacture of beverages	1%	2%
13	Manufacture of textiles	117%	129%
14	Manufacture of wearing apparels	2%	3%
15	Manufacture of leather and related products	<1%	<1%
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	<1%	1%
17	Manufacture of pulp, paper and paper products	1%	1%
18	Publishing, printing and reproduction of recorded media	<1%	<1%
19	Manufacture of coke and refined petroleum products	6%	25%
20	Manufacture of chemicals and chemical products	3%	5%
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	<1%	1%
22	Manufacture of rubber and plastic products	<1%	1%
23	Manufacture of other non-metallic mineral products	<1%	<1%
24	Manufacture of basic metals	<1%	<1%
25	Manufacture of fabricated metal products, except machinery and equipment	<1%	<1%
26	Manufacture of computer, electronic and optical products	3%	4%
27	Manufacture of electrical equipment	<1%	1%
28	Manufacture of machinery and equipment n.e.c.	1%	1%
29	Manufacture of motor vehicles, trailers and semi-trailers	1%	1%
30	Manufacture of other transport equipment	1%	2%
31	Manufacture of furniture	<1%	<1%
32	Other manufacturing	<1%	<1%
35	Electricity, gas, steam and air conditioning supply	<1%	<1%
36	Water collection, treatment and supply	<1%	<1%
37	Sewerage	0%	0%

NACE classification followed in this study is NACE Rev 2 - a European statistical classification system of economic activities corresponding to International Standard Industrial Classification of All Economic Activities (ISIC) Rev.4.

Table 35: Objectives of innovations

How important were each of the following objectives for your activities to develop product or process innovations during the three years 2008 to 2010?   **Possible answers: High, Medium, Low, Not relevant**
Increase range of goods or services
Enter new markets or increase market share
Improve quality of goods or services
Improve flexibility for producing goods or services
Reduce labour costs per unit output
Reduce material and energy costs per unit output or improve health or safety of your employees

Notes. This is the list of answers that are common to every CIS questionnaires except the 2008 CIS questionnaire.

Table 36: Selection of firms based on labor share

	Dependent variable: Log (TFP)			
	OLS			
	Firm's labor share of the available plants			
	0%	50%	75%	90%
	(1)	(2)	(3)	(4)
Environmental effort (%)	-0.0000	0.0002*	0.0002	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.001)
Financial independance	0.0205***	0.0166***	0.0148***	0.0176***
	(0.0030)	(0.0047)	(0.0048)	(0.0045)
Age	0.0003	0.0004	-0.0001	-0.0001
	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Trade competition (%)	0.0015	0.0030	0.0.0017	0.0019
	(0.0027)	(0.0027)	(0.0025)	(0.0028)
Industry concentration	-0.0073	0.0503	0.0310	-0.0791
	(0.0687)	(0.0921)	(0.0890)	(0.0853)
Industry × year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Number of observations	54,402	22,025	20,334	17,950
Number of firms	15,719	10,630	10,129	9,307
Average number of observations per firm	3.5	2.1	2.0	1.9

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 37: Coefficients of correlation between different measures of total factor productivitiy

	Labor is measured in working hours				Labor is measured in wages			
	Inputs exclude energy		Inputs include energy		Inputs exclude energy		Inputs include energy	
	Nominal turnover	Real turnover	Nominal turnover	Real turnover	Nominal turnover	Real turnover	Nominal turnover	Real turnover
	TFP_1	TFP_2	TFP_3	TFP_4	TFP_5	TFP_6	TFP_7	TFP_8
TFP_1	1 (8,278)							
TFP_2	0.985*** (4,208)	1 (4,208)						
TFP_3	0.982*** (4,680)	0.955*** (2,508)	1 (4,680)					
TFP_4	0.954*** (2,508)	0.977*** (2,508)	0.977*** (2,508)	1 (2,508)				
TFP_5	0.940*** (8,277)	0.938*** (4,208)	0.929*** (4,679)	0.926*** (2,508)	1 (8,277)			
TFP_6	0.922*** (4,209)	0.945*** (4,208)	0.906*** (2,508)	0.939*** (2,508)	0.985*** (4,209)	1 (4,209)		
TFP_7	0.919*** (4,679)	0.913*** (2,508)	0.942*** (4,679)	0.943*** (2,508)	0.983*** (4,679)	0.958*** (2,508)	1 (4,679)	
TFP_8	0.893*** (2,508)	0.927*** (2,508)	0.923*** (2,508)	0.955*** (2,508)	0.958*** (2,508)	0.979*** (2,508)	0.979*** (2,508)	1 (2,508)

Notes. $***p < 0.01$. Number of observations in parenthesis. Data from the panel data set for year 2006. The TFP measures are computed in logarithmic term as explained in section 4.3.1.

Table 38: First stage estimation: Environmental effort and productivity

	Dependent variable: Environmental effort (%)
Environmental effort (%) made by similar firm	0.0141**
	(0.0062)
Financial independence	0.3960**
	(0.1595)
Age	0.0773**
	(0.0335)
Trade competition (%)	0.1046
	(0.1473)
Industry concentration	-2.7091
	(3.9926)
Year dummies	Yes
Industry × year dummies	Yes
Region × year dummies	Yes
Firm fixed effects	Yes
F statistic	5.14**
Number of observations	43,018
Number of firms	8,417
Average number of observations per firm	5.1

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
Regions refers to the French 'departements'
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 39: Functional form of environmental effort

	OLS	
	Dependent variable: Log (TFP)	
	Transformation of environmental effort	
	Level	Log
	(1)	(2)
Environmental effort (%)	-0.0001	-0.0003
	(0.0001)	(0.0007)
Financial independence	0.0256***	0.0256***
	(0.0040)	(0.0040)
Age	0.0007	0.0007
	(0.0007)	(0.0007)
Trade competition (%)	0.0044	0.0044
	(0.0039)	(0.0039)
Industry concentration	0.0012	0.0015
	(0.0839)	(0.0839)
Industry-period dummies	Yes	Yes
Firm fixed effects	Yes	Yes
Number of observations	32,708	32,708
Number of firms	9,831	9,831
Average number of observations per firm	3.3	3.3

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 40: Regression without influential observations

	TSLS	
	Dependent variable: Log (TFP)	
	Top 10% Environmental effort	Top 10% & bottom 10% Log (TFP)
	(1)	(2)
Environmental effort (%)	0.0053	0.0066
	(0.0112)	(0.0042)
Financial independence	0.0230***	0.0119***
	(0.0034)	(0.0033)
Age	-0.0003	-0.0009
	(0.0004)	(0.0006)
Trade competition (%)	-0.0014	-0.0019
	(0.0020)	(0.0017)
Industry concentration	0.0579	-0.0514
	(0.0828)	(0.0469)
Year dummies	Yes	Yes
Firm fixed effects	Yes	Yes
First-stage IV coefficient	0.0057***	0.0153**
Kleibergen-Paap rk LM statistic	9.55***	4.84**
Number of observations	38,263	34,993
Number of firms	7,892	7,193
Average number of observations per firm	4.8	4.9

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 41: Environmental effort and productivity

	Dependent variable: Log (TFP) OLS (1)
Environmental effort (%)	-0.0000
	(0.0001)
Financial independence	0.0195***
	(0.0030)
Age	0.0004
	(0.0005)
Trade competition (%)	0.0015
	(0.0026)
Industry concentration	-0.0048
	(0.0694)
Year dummies	Yes
Industry × year dummies	Yes
Region × year dummies	Yes
Firm fixed effects	Yes
Number of observations	54,402
Number of firms	15,719
Average number of observations per firm	3.5

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
Regions refers to the French 'departements'
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 42: Estimation by manufacturing sector

NACE code	Sector	Coefficient	Standard Error	Number of observations	Number of firms
10	Food products	0.0006*	(0.0003)	2,754	1,400
11	Beverages	-0.0016	(0.0014)	339	166
12	Tobacco products	Insufficient number of observations			
13	Textiles	-0.0006	(0.0005)	199	161
14	Wearing apparels	-0.0004	(0.0056)	822	281
15	Leather and related products	-0.0002	(0.0002)	4,846	1,368
16	Wood and of products of wood and cork	-0.0002	(0.0006)	417	316
17	Pulp, paper and paper products	0.0000	(0.0003)	1,982	844
18	Publishing, printing and reproduction of recorded media	0.0002	(0.0004)	773	500
19	Coke and refined petroleum products	-0.0001	(0.0003)	368	123
20	Chemicals and chemical products	0.0000	(0.0004)	2,014	1,028
21	Basic pharmaceutical products and pharmaceutical preparations	0.0004**	(0.0002)	2,084	582
22	Rubber and plastic products	-0.0003	(0.0002)	2,251	1,288
23	Other non-metallic mineral products	-0.0009	(0.0009)	842	498
24	Basic metals	-0.0003	(0.0002)	5,929	1,433
25	Fabricated metal products, except machinery and equipment	0.0001	(0.0002)	6,187	2,558
26	Computer, electronic and optical products	0.0001	(0.0004)	1,831	716
27	Electrical equipment	-0.0001	(0.0002)	2,254	638
28	Machinery and equipment n.e.c.	0.0007	(0.0002)	6,134	2,831
29	Motor vehicles, trailers and semi-trailers	0.0002	(0.0004)	3,829	1,254
30	Other transport equipment	-0.0004	(0.0013)	302	148
31	Furniture	-0.0007	(0.0006)	1,777	558
32	Other manufacturing	-0.0008	(0.0007)	1,191	467
33	Repair and installation of machinery and equipment	0.0001	(0.00076)	1,415	594
34	Electricity, gas, steam and air conditioning supply	-0.0004	0.0003	1,465	368
35	Electricity, gas, steam and air conditioning supply	0.0002	(0.0009)	909	250
36	Water collection, treatment and supply	-0.0005	(0.0003)	1,447	496
37	Sewerage	Insufficient number of observations			

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
OLS fixed-effect point estimate and standard errors for the environmental effort parameter of equation (4.1)
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 43: Environmental effort and scale of the innovation using development dummy

	Dependent variable	
	R&D expenditure	Innovation (0/1)
	PPML	Probit
	(1)	(2)
Environmental effort (%)	-0.0054	-0.0032
	(0.0089)	(0.0034)
Log (number of employees)	1.317***	-0.0655
	(0.0665)	(0.0455)
Financial independence	0.0181	
	(0.0417)	
Age	-0.0121***	0.0022
	(0.0043)	(0.0024)
Trade competition	-0.1899**	-1.0339
	(0.0757)	(2.4923)
Industry concentration	-6.7867***	-4.6025*
	(2.1883)	(5.4755)
R&D expenditure		0.3470***
		(0.0127)
Industry $\times$ year dummies	Yes	Yes
Firm fixed effects	No	No
Number of observations	5,182	3,678
Number of firms	3,163	2,710
Average number of observations per firm	1.6	1.4

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 44: Environmental effort and scale of the innovation using IV approach

	Dependent variable	
	R&D expenditure	Green innovation (%)
	Control function	TSLS
	(1)	(2)
Environmental effort (%)	-0.2443	0.1048
	(0.1948)	(0.4031)
Log (number of employees)	1.296***	1.8276***
	(0.0665)	(0.3522)
Financial independence	0.0780	0.1834
	(0.0682)	(0.2206)
Age	-0.0144**	0.0014
	(0.0060)	(0.0141)
Trade competition (%)	-0.0758***	0.0039
	(0.0225)	(0.0801)
Industry concentration	0.6257	2.2538
	(0.6390)	(3.6456)
Period dummies	Yes	Yes
Industry-period dummies	No	No
Firm fixed effects	No	No
First-stage IV coefficient	0.0604***	0.0639***
Kleibergen-Paap rk LM statistic		8.14***
Number of observations	4,838	3,678

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 45: Placebo tests for the direction of innovation

	OLS				
	Dependent variable: direction of the innovation				
	Product range	New market	Quality	Flexibility	Labor saving
	(1)	(2)	(3)	(4)	(5)
Environmental effort (%)	-0.061*	-0.043**	0.007	-0.018	0.013
	(0.034)	(0.018)	(0.025)	(0.015)	(0.017)
Log (number of employees)	-1.420***	-0.851***	-0.454***	0.250*	0.515***
	(0.239)	(0.160)	(0.142)	(0.135)	(0.123)
Financial independence	-0.383	-0.312**	-0.047	0.217	0.321*
	(0.307)	(0.157)	(0.132)	(0.127)	(0.163)
Age	0.013	-0.007	-0.007	0.006	-0.001
	(0.016)	(0.011)	(0.009)	(0.009)	(0.009)
Trade competition (%)	0.304	0.224	0.289	0.094	-0.372
	(0.403)	(0.255)	(0.239)	(0.225)	(0.265)
Industry concentration	-37.617*	-22.091	-9.255	-13.974	36.123**
	(21.606)	(17.063)	(16.392)	(15.615)	(17.983)
Industry-period dummies	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
Number of observations	4,538	4,538	4,538	4,538	4,538
Number of firms	2,217	2,217	2,717	2,717	2,717
Average number of observations per firm	2	2	2	2	2

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 46: Green innovation and total factor productivity using different functional forms

	OLS		
	Dependent variable: TFP		
	Transformation of the R&D variable		
	$sinh^{-1}x$	$\ln x$	
	(1)	(2)	(3)
R&D expenditure	0.0079***	0.0107***	0.0179***
	(0.0014)	(0.0021)	(0.0031)
Green innovation (%)	-0.0004*	-0.0005**	0.0014**
	(0.0002)	(0.0002)	(0.0006)
R&D expenditure × Green innovation (%)			-0.0003***
			(0.0001)
Financial independence	0.0152***	0.0151**	0.0150**
	(0.0056)	(0.0060)	(0.0060)
Age	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)
Trade competition (%)	0.0044	0.0062	0.0063
	(0.0129)	(0.0131)	(0.0129)
Industry concentration	0.4547	0.4582	0.4750
	(0.5140)	(0.5095)	(0.5104)
Industry-period dummies	Yes	Yes	Yes
Firm fixed effects	No	No	No
Number of observations	11,049	10,059	10,059
Number of firms	7,573	6,875	6,875
Average number of observations per firm	1.5	1.5	1.5

$sinh^{-1}x = \ln(x + \sqrt{1 + x^2})$ is the inverse hyperbolic sin.
Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 47: Compliance operating costs and profitability, pooled and first-difference estimates

	Dependent variable: Operating margin			
	OLS		OLS on 2010-2004	
	(1)	(2)	(3)	(4)
Log (Share of environmental expenditure)	-0.288***	-0.159*	-0.776***	-0.711**
	(0.090)	(0.086)	(0.283)	(0.279)
Operating margin t - 1	0.730***	0.729***		
	(0.054)	(0.055)		
Log (TFP)	3.095***	3.677***	7.820***	8.088***
	(0.424)	(0.440)	(1.953)	(2.001)
Log (Market share)	0.320***	0.259***	1.385**	1.241**
	(0.073)	(0.074)	(0.571)	(0.582)
Financial independence	0.285*	0.366**	0.784***	0.810***
	(0.148)	(0.144)	(0.297)	(0.297)
Log (Average wage)	-1.856***	-1.940***	-6.366***	-6.521***
	(0.502)	(0.501)	(1.702)	(1.703)
Log (Share of tax expenditure)		-1.224***		-1.835**
		(0.225)		(0.820)
Firm fixed effects	No	No	Difference	Difference
Industry × year dummies	Yes	Yes	Yes	Yes
Number of observations	5,653	5,652	1,250	1,250
Number of firms	4,762	4,761	1,250	1,250
Average number of observations per firm	1.2	1.2	1	1

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
Two digits NACE 2 industry dummies
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Table 48: Compliance operating costs and profitability using another functional form

	Dependent variable: Operating margin
	OLS
Share of environmental expenditure	-34.596*
	(18.097)
Operating margin t - 1	0.742***
	0.054)
TFP	0.578***
	(0.116)
Market share	0.021
	(0.013)
Financial independence	0.252*
	(0.146)
Average wage	-0.001*
	(0.001)
Firm fixed effects	No
Industry × year dummies	Yes
Number of observations	5,653
Number of firms	4,762
Average number of observations per firm	1.2

Clustered standard errors robust to heteroskedasticity and autocorrelation in parentheses
Two digits NACE 2 industry dummies
All columns include a constant (not reported) $***p < 0.01, **p < 0.05, *p < 0.1$

Figures

Figure -8: World waste trade as measured with import statistics, export statistics, and our maximum methodology

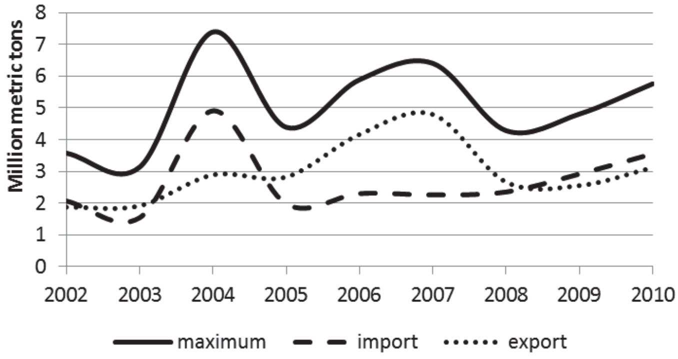


Figure -9: GDP and the total amount of waste imported

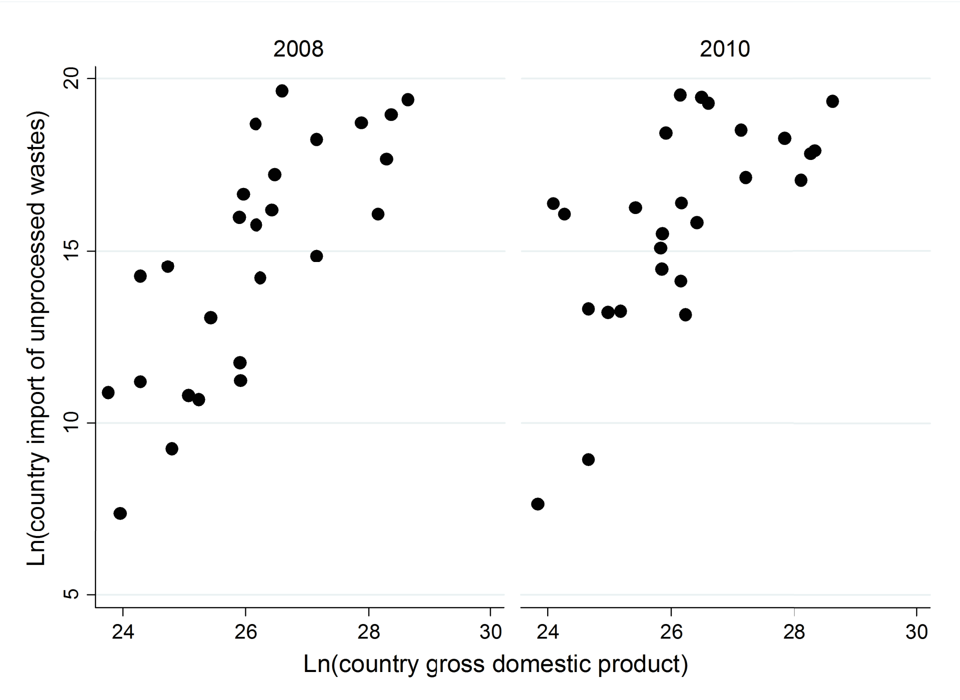
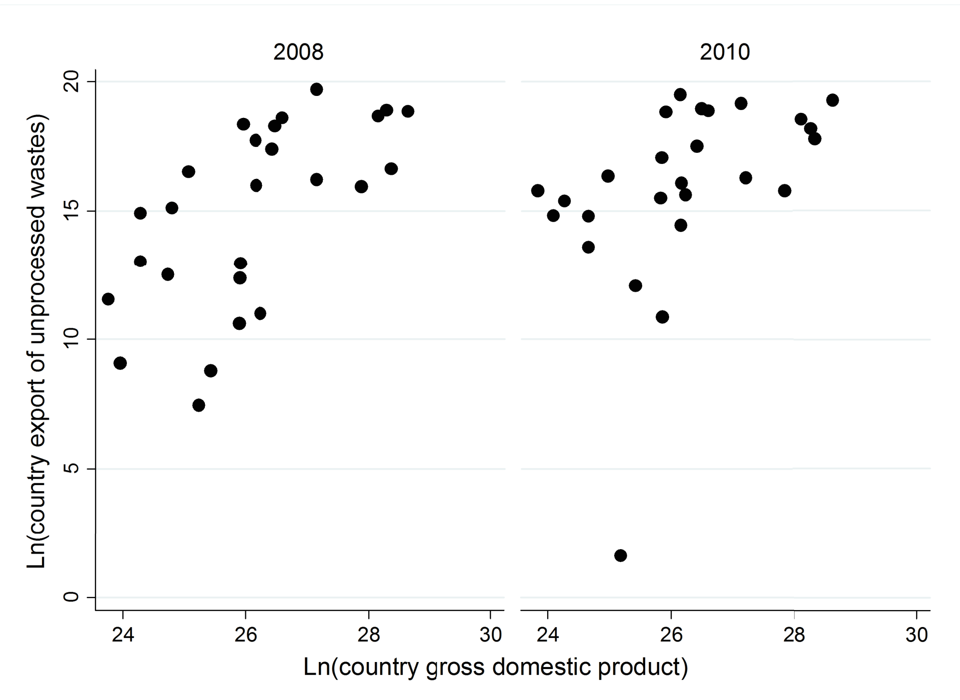


Figure -10: GDP and the total amount of waste exported



Les effets des politiques environnementales sur le commerce international des déchets, l'innovation verte, et la compétitivité, dans un monde globalisé

RESUME : Les politiques environnementales unilatérales, destinées à corriger les défaillances de marché, peuvent échouer dans un monde globalisé. Cette thèse se compose de quatre chapitres qui examinent aux moyens de méthodes économétriques plusieurs mécanismes en jeu dans l'effet de la libéralisation des échanges internationaux sur l'environnement. Dans le premier chapitre de cette dissertation, je trouve qu'une différence entre les taux de taxes sur la gestion des déchets a un impact non négligeable sur la quantité de déchets exportés des pays à fort niveau de taxation vers les pays à faible niveau de taxation. Ce résultat illustre l'impact néfaste que peuvent avoir, en situation de libre échange, les comportements stratégiques de type « nivellement par le bas ». Dans le second chapitre, je trouve que les politiques de recyclages, qui stimulent la production locale de matières premières secondaires, ont un impact négatif substantiel sur les importations de matières premières métalliques. Il est nécessaire de prendre en compte cet impact positif lors de l'évaluation des politiques de recyclage. Dans le troisième chapitre, je trouve que la capacité d'importer des matériaux en provenances des pays a bat coût a réduit de manière drastique l'innovation verte dans les pays à coût de production élevé durant les dernières décennies. Ce résultat suggère que la libéralisation des échanges a ralenti l'abattement des émissions mondiales. Dans le dernier chapitre, je teste la majorité des hypothèses formulées par Porter et van der Linde. Mon analyse empirique rejette l'hypothèse de Porter bien que l'impact négatif des réglementations environnementales sur la profitabilité des firmes soit plutôt faible.

Mots clés : Politique environnementale, commerce international, innovation verte, recyclage, déchets dangereux, compétitivité

The effects of environmental regulations on waste trade, clean innovation, and competitiveness in a globalized world

ABSTRACT : In a globalized world, unilateral environmental policies may fail to correct market failures from a global point of view. This dissertation is composed of four essays that examine, using econometric methods, several mechanisms at play in the effect of international trade liberalization on the environment. In the first chapter of this dissertation, I find that a higher asymmetry in the waste taxes is associated with a non-negligible amount of waste exported from strict countries to lax countries. This result illustrates the harmful impact that "race to the bottom" behaviours can have under free trade. In the second chapter, I find that recycling policies substantially reduce country dependence on foreign raw materials by stimulating domestic production of secondary raw materials. It is necessary to include this positive side effect when evaluating recycling policies. In the third chapter, I find that trade with low-cost countries may have significantly reduced green innovation in high production cost countries during the last decades. This result suggests that trade liberalisation has slowed down the abatement of global emissions. In the last chapter, I test a major part of the assumptions made in the seminal work of Porter and van der Linde. I find evidence against the Porter Hypothesis although the negative impact of regulations on firm profitability is rather small.

Keywords : Environmental regulation, international trade, green innovation, recycling, hazardous waste, competitiveness

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